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A longitudinal study of B2B customer engagement in LinkedIn: The role of brand personality

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ABSTRACT

In business-to-business (B2B) settings, social media provide a novel context for investigating customer engagement. While B2B firms are increasingly investing in social media, there is limited understanding about the type of content to be published and how customers may react to their posts. The authors address these research gaps by developing a conceptual framework that relates posts' brand personality dimensions (sincerity, excitement, competence, sophistication, and ruggedness) to customer engagement. Using data from a small-sized Chilean-Swiss consultancy firm accounting for 114 weeks of LinkedIn activity, the authors specify a VAR model with exogenous variables (VARX). Focusing on the cumulative elasticities, the study uncovers the engagement mechanisms of customers. The results show that an increase in impressions (exposure) leads to an increase in likes, clicks, and shares (perceptions), an increase in clicks leads to an increase in new followers (actions), and an increase in new followers leads to an increase in impressions. Furthermore, the results indicate that an increase in posts' excitement leads to an increase in impressions and likes, an increase in posts' competence leads to an increase in clicks, and an increase in posts' ruggedness leads to an increase in new followers.

1. Introduction

Business-to-business (B2B) service firms are increasingly adopting social media as part of their marketing mix (Bill, Feurer, & Klarmann, 2020). Indeed, B2B service firms' digital marketing budgets have grown consistently during the last few years, and a 10% growth is expected for the next 12 months, according to a recent CMO Survey (Moorman, 2020). This expected growth is superior to B2B products (1.5%), B2C products (−4.3%), and B2C services (−8.8%; see Moorman 2020, p. 31). Moreover, due to the ongoing pandemic, firms perceive an increased value placed on digital experiences at the customer level. Firms anticipate that this customer behavior change (relative to a pre-pandemic state) will remain valuable indefinitely (Moorman, 2020, p. 16). Social media deliver many experiences (Itani, Agnihotri, & Dingus, 2017; Jackson 2018), as online engagement represents a logical step in the evolution of customer relationship management (Rapp & Panagopoulos, 2012; Venkatesan, 2017). Due to their limited resources, small- and medium-sized enterprises (SMEs) see social media as an opportunity (Brink, 2017). However, extant research is limited on the content published in social media (Bill et al., 2020) and the mechanisms that account for the buyer–seller interaction (Ghekiere & Zinkevich, 2019). Moreover, B2B social media research is focused on large-sized firms (see Web Appendix A). Hence, the objective of this paper is to determine how social media content relates to customer engagement behaviors in a B2B service SME setting.

In this study, we develop and test a comprehensive framework of B2B customer engagement in social media, taking into account the relationship between distinct content approaches and myriad dimensions of customer engagement. Based on a *non-linear purchasing decision view* that involves the different forms of communication in an online system (e.g., Vieira et al., 2019), and the *brand personality* concept that entails five dimensions: (1) sincerity, (2) excitement, (3) competence, (4) sophistication, and (5) ruggedness (e.g., Aaker, 1997), we establish our theoretical lens. The buyer–seller interaction setting is limited to LinkedIn, since this platform is the social network most used by B2B firms (Jackson, 2018) and no previous study explores its users' engagement. Different social media have diverging functionality and positioning, making it necessary to deeply investigate the particular mechanisms of individual platforms (Salo, 2017). LinkedIn offers a complex set of engagement options, allowing customers to interact with sellers. On one hand, the platform feed disseminates posts selectively to users who can engage by looking at the posts, creating an *impression*. On the other

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hand, users can express their perceptions toward posts through explicit behaviors such as (1) *liking* (and five similar reactions) the post, (2) *clicking* on the post, (3) *sharing* the post, and (4) *commenting* on the post. In addition, users accounting for their experience with the supplier posting can reach a superior level of engagement and become *followers*, which is considered the ultimate goal in B2B social media and represents a proactive behavior (e.g., Katona & Sarvary, 2014). In this vein, our proposed framework (Fig. 1) attempts to address the following research questions: (1) How are the different customer engagement behaviors (i.e., user's reaction mechanisms) associated? (2) Which brand personality dimensions (associated with individual posts) lead to more customer engagement behaviors? and (3) What are the cumulative effects (i.e., elasticities) of posts' brand personality dimensions and users' engagement behavior?

Using data from a Chilean-Swiss consultancy SME operating in two countries, we develop a vector autoregressive econometric model with control (exogenous) variables (VARX) of the LinkedIn experience, including posts' brand personality and customer engagement behaviors (exposure, perceptions, and actions). The data consist of posts made by the firm's corporate LinkedIn account. The focal firm serves B2B firms directly, facing a challenging sales process since most of the services are not previously budgeted and require high adaptation to customer requirements. The selected firm provides an appropriate setting to test the proposed framework because no other social media are used by this firm and its offerings includes both short-term services (e.g., monthly training events) with relatively spontaneous demand and long-term services (e.g., strategy formulation and execution) with project-based demand. The dataset spans about two years of weekly information, considering seasonality, lagged variables, and trends effects, which are common elements in longitudinal analysis (e.g., Hewett, Rand, Rust, & Van Heerde, 2016; De Vries, Gensler, & Leeflang, 2017). The VARX model allows capturing both contemporaneous and persistent effects (Kim & Hanssens, 2017), enhancing practical utility. The longitudinal feature of the selected model is one of the differentiating factors of this study due to the prevailing cross-sectional, qualitative, and conceptual focus on social media in the literature (see Web Appendix A), which ignores opportunities related to the big data nature of such platforms (Meire, Ballings, & Van den Poel, 2017). The longitudinal feature of our data allows us to understand the correct sequence of events, thereby facilitating a better exploration of causal relationships, and provides insights into the proliferation of effects across different time periods.

We contribute to research in three major ways. First, we extend the *circular decision journey* view (see Lingqvist, Plotkin, & Staley, 2015) by investigating a particular social media platform and the desired customer engagement behaviors (e.g., Salo, 2017). We provide an in-depth explanation of the interaction mechanisms resulting from posting on the LinkedIn feed. Through scrutinizing the different customer behaviors in the platform, we explain the inner mechanisms to build social capital by capturing more followers, who are actors prone to information sharing, resource exchange, and collaboration (Prodromou, 2015). Hence, in this paper, we respond to calls for research in the social media-social capital intersection (e.g., Agnihotri, 2020). Our findings indicate that *impressions* (exposure) are the cornerstone for further social exchange, as a 1% increase in impressions leads to 0.581%, 0.896%, and 0.063% increases in likes, clicks, and shares, respectively. No other variable has that many repercussions. Surprisingly, the results indicate that the impact of impressions can persist more than any other engagement effect with a contemporaneous impact on likes and clicks that persists for three to four weeks.

Second, our findings suggest a cyclical engagement effect commencing with exposure and leading to manifestations of perceptions, which, in turn, leads to actions. This discovery extends the current view constituting the B2B marketing communication effects (Gilliland & Johnston, 1997). Our analysis shows that a 1% increase in likes leads to 0.128% and 0.171% increases in shares and comments, respectively; and a 1% increase in clicks leads to 0.138% and 0.131% increases in comments and new followers, respectively. Interestingly, a 1% increase in new followers leads to a 0.115% increase in impressions, driving a beneficial cycle. Therefore, we suggest that all three types of engagement behavior are valuable to sustain a growing social media interactive system. Managers can use this chain of events to map the most effective paths to cultivate a rich pool of followers.

Third, we contribute to the branding-social media interface. While research on brand personality often examines outcomes like perceived trust (Sung & Kim, 2010) or customer satisfaction and loyalty (Brakus, Schmitt, & Zarantonello, 2009), we examine posts' brand personality influence on customer engagement in LinkedIn. Our findings indicate that a 1% increase in posts' excitement leads to 0.173% and 0.079% increases in impressions and likes, respectively. Moreover, a 1% increase in posts' competence leads to a 0.131% increase in clicks. Also, a 1% increase in posts' ruggedness leads to a 0.324% increase in new followers. Hence, we suggest that the projected brand personality of a post (via its content and graphic design) is an important tenet in social media communication. The identified brand personality dimensions may allow B2B SMEs to reconsider their positioning statement and overall advertising strategy.

2. Theoretical background

2.1. Emergence of a non-linear sales process

Traditional sales literature in the B2B realm is predominantly

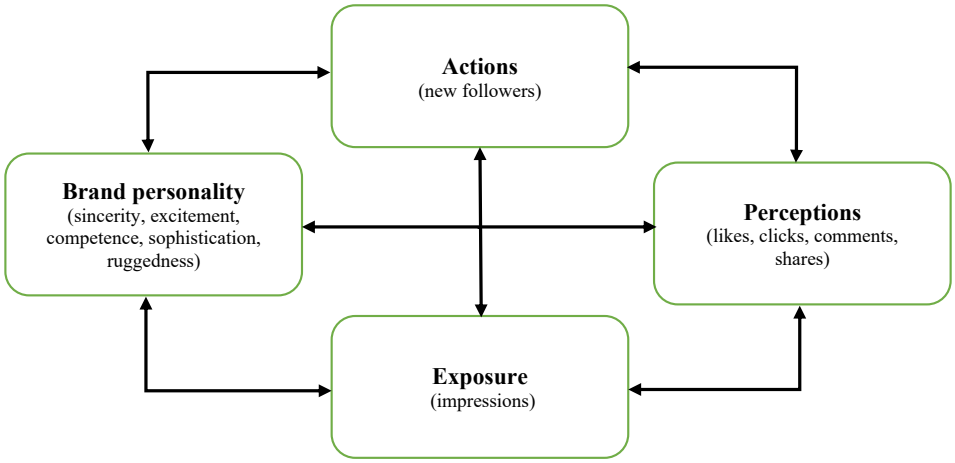

Fig. 1. Conceptual framework.

focused on a linear selling process comprising different stages (e.g., Dubinsky, 1981). The "seven steps of selling" became central in B2B sales literature, consisting of the following stages: (1) Prospecting, (2) Pre-approach, (3) Approach, (4) Presentation, (5) Overcoming objections, (6) Close, and (7) Follow-up (Moncrief & Marshall, 2005; Marshall et al., 2012). Recent academic research suggests that B2B sales organizations have adapted their sales processes for success in the new digital era with empowered customers (Bowen, Lai-Bennejean, Haas, & Rangarajan, 2021, p. 166). Compared with more traditional seller-centric models assuming a waiting customer, new sales models build over a proactive customer participating in value co-creation in networks and systems (Hartmann, Weiland, & Vargo, 2018). Hence, the traditional way of selling is migrating toward a non-linear sales approach to fit digitally-driven sales practices, including the implementation of social media in B2B settings (Agnihotri, Dingus, Hu, & Krush, 2016; Ancillai, Terho, Cardinali, & Pascucci, 2019; Bowen et al., 2021).

A digital era B2B customer follows a purchase-consumption circular loop. With the proliferation of information in the digital space, the customer is more informed, enabling firms to start with a narrower consideration set (Vieira et al., 2019, p. 1100). The digital revolution has transformed once-predictable B2B customer purchasing paths from linear into a more circular pattern of touch-points, as customers research, evaluate, select, and share experiences about products and services in online networks (Lingqvist et al., 2015). In the emerging purchasing circular process, B2B firms must engage with customers throughout their journey (Vieira et al., 2019). Using social media it is possible to follow the lead of customers rather than force them to follow the sales organization (Lingqvist et al., 2015). Overall, the ongoing shift and widespread adoption of social media have changed the old paradigm of the seven steps of selling (Andzulis et al., 2012; Bowen et al., 2021).

2.2. Social media adoption in B2B SMEs

Social media are broadly defined as "a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0 and allow the creation and exchange of user-generated content" (Kaplan & Haenlein, 2010, p. 61). In B2B practice, social media refer to specific online platforms where buyers and sellers communicate, such as discussion forums, blogs, wikis, social networks, and multimedia sites, with Facebook, LinkedIn, Twitter, and YouTube being the most accepted (Guesalaga, 2016). Scholarly inquiries indicate that social media can generate higher brand attitudes and purchase intentions than more traditional digital media (Siamagka et al., 2015, p. 90). However, extant literature stresses that social media adoption has been slower in B2B settings than in B2C settings (e.g., Michaelidou, Siamagka, & Christodoulides, 2011; Iankova et al., 2019). Despite being inexpensive to implement, social media require identifying the communication appeals relevant for the industry and organization, and accounting for the human resources necessary to support continuous content generation (Andzulis, Panagopoulos, & Rapp, 2012).

Within the B2B realm, less attention has been paid to the use of social media by SMEs than by large firms (Wang, Pauleen & Zhang, 2016). Recent findings indicate that SMEs adopt social media marketing for reasons similar to larger firms (e.g., compatibility, perceived usefulness, perceived ease of use, and cost reductions; Chatterjee & Kar, 2020; Eid, Abdelmoety, & Agag, 2019). B2B SMEs suffer from a lack of time and available resources, which can be overcome by using Internet communication tools such as social media (Brink, 2017). Wang et al. (2016) found that three social media capabilities are influential in improving B2B SME communication performance: (1) transmission velocity, (2) parallelism, and (3) rehearsability. Michaelidou et al. (2011) indicated that attracting new customers is key for B2B SMEs' social media adoption. Similarly, extant research shows that B2B SMEs embrace social media as a tool for identifying new business opportunities and quality business contacts in international settings (Fraccastoro, Gabrielson, & Pullins, 2021; Eid et al., 2020). Nevertheless, B2B SME top management is still hesitant to fully launch social media usage (Salo, 2017). In this regard, Brink (2017) notes that the application of social media requires B2B SME managers to enable open business model innovation and to integrate central and distributed leadership.

One key barrier limiting the adoption of social media by B2B SMEs is the marketers' poor understanding of how to use these platforms for marketing purposes (Lacka & Chong, 2016). Low social media "know-how" creates a negative attitude among marketers toward the usefulness of social media platforms and hinders their adoption (Michaelidou, Siamagka, & Christodoulides, 2011). An additional concern is the likelihood of confidential or sensitive information leakage, which discourages B2B marketers from adopting social media (Jussila, Kärkkäinen, & Aramo-Immonen, 2014). Another interesting aspect for B2B SMEs is associated with the customer's social media adoption. Keinänen and Kuivalainen (2015) indicate that the managers of an IT service firm are reluctant to use social media for business purposes, but chances increase when they (1) use social media as individuals, (2) have colleagues' support for using social media, and (3) are younger and in a lower hierarchical position. Notably, despite the aforementioned barriers, more B2B SMEs are aiming to increase their investment in social media marketing (Brink, 2017; Lacka & Chong, 2016), particularly in service settings (Moorman 2020). Even low innovative B2B firms have followed the trend of social media usage in support of their marketing strategies (Bump, 2020). Hence, understanding the mechanisms (i.e., engagement options) available for customers to react to social media content is highly valuable for service SMEs in B2B settings.

3. Conceptual framework

3.1. LinkedIn as a platform for buyer–seller interaction

LinkedIn is the most popular and valued social media platform for B2B marketers (Jackson, 2018; Keinänen & Kuivalainen, 2015; Siamagka et al., 2015), providing a way for firms to connect their corporate identity with their corporate audiences (Prodromou, 2015). Since its creation in 2003, LinkedIn has grown a population of about 750 million users with strong penetration in the United States, Europe, India, and Latin America (e.g., Ghekiere & Zinkevich, 2019; Prodromou, 2015). LinkedIn attracts millions of firms with about 99% of them being classified as SMEs (Burt, 2021). B2B SME managers on LinkedIn connect, converse and form relationships with each other, and they associate with brands within their industries to learn and grow together and to share professional content (Diba, Vella, & Abratt, 2019, p. 1485). Similarly, Itani et al. (2017) indicate that LinkedIn may assist in publicizing names of true decision-makers and buyers within an organization.

LinkedIn plays an active role in educating a firm's prospects in B2B SME settings (Fisher, 2020). For this reason, a stream of researchers is specifically interested in social media content and how B2B customers react to it (Katona & Sarvary, 2014). According to Juntunen, Ismagilova, and Oikarinen (2020), *content* "denotes the different forms of material published on social media, including text, photos, voice recordings, and videos" (p. 630). Such content should be analyzed from a knowledge-based view for integrating social media marketing into the overall strategic framework of sales and marketing, operating in business markets (Agnihotri, 2020, p. 292). Knowledge is a key organizational resource that contributes to value co-creation in B2B relationships (Powell & Swart, 2010) and can help in crafting a unique selling position to achieve competitive advantage (Hollebeek, 2019).

The content achieves *meaning* only through the viewer's interpretation and, thus, new knowledge is created iteratively via online social behaviors of customers on the LinkedIn feed. In other words, the content communicated on LinkedIn and the user's engagement behaviors in response to the content altogether represent a type of social interaction contributing to the formation of a digital *interactive network* rich in online social capital (Agnihotri, 2020). Despite its importance for B2B

SMEs, the *post configuration* and *characteristics* have not been previously explored in the academic literature (Ghekiere & Zinkevich, 2019). We theorize on the buyer–seller interaction by relating the attainable customer engagement behaviors to the brand personality of posts (see Fig. 1), following the idea of purchase decisions consisting of a circular process (e.g., Vieira et al., 2019).

3.2. Customer engagement behaviors in LinkedIn

Customer engagement is broadly defined as "a customer's motivationally driven, volitional investment of focal operant resources (including cognitive, emotional, and behavioral knowledge and skills), and operand resources (e.g., equipment) into brand interactions in service systems" (Hollebeek, Srivastava, & Chen, 2019, p. 167). Much conceptual and exploratory work exists on the role of customer engagement in B2C settings, but this work has yet to be validated in a social media context (Dessart, 2017), especially in B2B settings (Hollebeek, 2019). Customer engagement in the realm of social media refers to "the extent to which the organization's important customers are active in using social media tools" (Guesalaga, 2016, p. 75). Hence, B2B social media engagement is a context-specific occurrence of customer engagement (Dessart, 2017). LinkedIn as a platform allows social interaction and social connectedness, offering versatility to suppliers in achieving customer engagement (Agnihotri, 2020). In B2B practice, engagement behaviors take any form of reaction available in the social network (Juntunen et al., 2020). To establish a categorization of such reactions in LinkedIn, we conducted pre-study semi-structured qualitative interviews with 21 experienced buyers, discussing extant views of customer engagement manifestations in the literature (e.g., Hollebeek et al., 2019). In our sample, 71.4% of respondents were male. All the respondents were located in Schengen countries and reported an average age of 42.6 years with at least 10 years of purchasing-related experience in B2B settings. On average, each interview lasted for 52 min. The questions explored their familiarity with social media usage in buying scenarios, possible behaviors in response to LinkedIn posts, and the relationships across all the possible engagement behaviors (see Table 1 for details of the responses). We adapt Gilliland and Johnston's (1997) model of "Business-to-Business Marketing Communications Effects" to categorize the interview responses into three types of customer engagement behaviors (deriving from information processing) on LinkedIn.

Table 1
Possible behaviors in response to posts.

Quote	Interviewee	Code
"First of all, it is not possible to pay attention to all the posts in the LinkedIn feed…. A key initial behavior in my opinion is actually to see a post."	Male, 39 years old	Exposure
"I miss many posts because I do not scroll down much…Usually, I end up seeing only a small group of posts coming from suppliers every day."	Female, 45 years old	Exposure
"Once I have observed a post and processed its information, sometimes I may develop favorability or interest in the post. I may react by liking, clicking, sharing, or commenting."	Male, 47 years old	Perception
"Even though I do not do it every time, when I think that a post is valuable, I show my interest by sharing or liking it."	Male, 50 years old	Perception
"A much more complex decision is becoming a new follower of a supplier as this requires stronger motivation in my opinion than simply liking a post…. I think by becoming a follower, managers are sending a clear cue that they are captivated not merely by a post but by the firm's LinkedIn communication strategy."	Male, 36 years old	Action
"For me it is especially relevant to become a follower of a supplier. This action relates you as a buyer to the future messages (posts) of that vendor… To me it means that there is a connection."	Male, 32 years old	Action

Exposure. Impressions are the beginning of customer engagement in LinkedIn and occur when customers are exposed to a post on their feed. They represent a measure of customers' attention to a firm's post. When customers scroll down their LinkedIn feed, they can stop and see updates (posts) generated by their network. Seeing an update once counts as an impression. Formally, LinkedIn defines impressions as the total number of times at least 50% of a post was seen for more than 300 ms (Sehl & Baird, 2020). Impressions relate to the beginning of the sales process as they help in the creation of brand awareness (Prodromou, 2015). This metric helps firms understand the reach of their posts, which, in turn, leads firms to comprehending whether their updates are resonating with the target audience (Fisher, 2020). We label impressions as *exposure* since impressions are the first point of contact between a user and a firm's post. This exposure to the post leads to processing of the post by the users through their attention to the post (McInnis & Jaworski, 1989).

Based on the digital behavior of customers, impressions are structurally important for building an online brand community (Prodromou, 2015). Indeed, a research stream on social media suggests a so-called 1/9/90 rule to explain that only about 1% of users actively create content, another 9% participate by commenting, clicking, or sharing content, and the other 90% simply watch, look, and read without responding (Ghekiere & Zinkevich, 2019). In other words, the vast majority of a firm's customers will see the posts but may not further engage with the posts. They will read and comprehend the content of the posts and keep on scrolling, meaning that a firm's target audience not *liking* its posts does not necessarily mean they do not "experience" the content (Ghekiere & Zinkevich, 2019).

Perceptions. Exposure followed by attention leads to allocation of cognitive resources by the user toward the stimuli (posts) which results in formation of perceptions in the minds of the users toward the stimuli (McInnis & Jaworski, 1989). The valence and strength of these perceptions depend on various factors such as relevance and fit of the stimuli to the user (e.g., appeal, creativity; Mora Cortez, Gilliland, & Johnston, 2020). LinkedIn allows users to express their perceptions toward posts through several overt behaviors such as likes, clicks, shares, and comments. These reactions represent a measure of customers' public expression of an affective response to a firm's post (e.g., Dessart, 2017). Such forms of engagement behaviors require several seconds (at a minimum) to be processed and executed by customers and involve a higher degree of cognitive processing of a post's content than impressions. These post level behaviors are a manifestation of users' perceptions towards posts and do not represent concrete actions towards the firm or the firm's LinkedIn account. For example, users may perceive a post to be interesting and may express it through *clicks* and *comments*. Thus, we label these behaviors as *perceptions*. Such customer engagement behaviors become visible on the platform (except for clicks) and thus the "digital footprint" of these types of behaviors is larger than for impressions (as forms of exposure).

Since July 2020, LinkedIn enables six kinds of *reactions* (like, celebrate, support, love, insightful, and curious). Overall, these *reactions*[1] are defined as "a set of expressions that offer members a way to more easily participate in conversations and communicate with their network" (LinkedIn, 2021). *Like* relates to the number of customers enjoying the post; *celebrate* relates to the number of customers offering recognition to the post; *support* relates to the number of customers empathizing with the post; *love* relates to the number of customers perceiving the post as heartwarming; *insightful* relates to the number of customers expressing that the post made a great point; and *curious* relates to the number of customers feeling intrigued by the post (LinkedIn, 2021).

[1] For simplicity, we called these reactions likes, because they represent the dominant form of reaction (Bump, 2020).

Clicks refers to the number of times that customers are clicking on the content, company name, or logo of the post (Sehl & Baird, 2020). Clicks represent an arousal in the customer interest either toward the content (by clicking on the content itself) or the focal firm (by clicking on the company name or logo). *Shares* refer to the number of times that customers are publishing the focal firm content on their LinkedIn feed (using the share option). Shares represent a way for customers to disseminate content that might be relevant for their network. In doing so, customers can use the @ functionality (i.e., *tagging*) to directly inform other managers/firms. Finally, customers can comment on a post by writing a response in the form of text (with the possibility to include icons and images). Hence, *comments* refer to the number of times that a post received a written statement from customers. Also, the focal firm, the original issuer, or other customers can reply to a comment, extending the dialogue.

Actions. Exposure and perceptions can potentially motivate a user to take *actions* towards the focal firm. Such behaviors are not at the post level and may result from exposure to one or several posts from the focal firm. LinkedIn offers one key opportunity for customers to further relate to firms by becoming a follower. The action of following a firm is completely volitional and proactive, and allows firms' posts to be displayed on the user's LinkedIn feed. Followers are explicitly informing a firm of their interest in learning about its services, staff, news, and other market related activities in the future, indicating a willingness to commit to a relationship with the firm. The procedure of becoming a follower is rather simple and can be executed using two different paths: (1) accessing the firm LinkedIn page and clicking on the blue follow button, and (2) when seeing a post of an interesting firm, the user can locate the cursor over the company name or logo and then click on following.[2] Nevertheless, the decision of becoming a follower entails elaborated thinking as it represents the acceptance of a firm as a valid source of information (Lessard, 2019).

Growing the firm's number of followers is deemed the most valuable marketing objective on LinkedIn (Prodromou, 2015). Followers are the lifeblood of a B2B service firm since they are the company's biggest digital fans (Bump 2020; Fisher 2020). Nevertheless, it is a difficult task to get followers, with the average LinkedIn user following just six companies (LinkedIn 2020b). Extant literature discusses a few reasons why followers are important (e.g., Ghekiere & Zinkevich, 2019). For instance, followers are 95% more likely to respond to a contact from one of the firm employees than a non-follower (LinkedIn, 2020b). Therefore, investigating how B2B marketers can step up the number of followers is essential for a more complete understanding of the LinkedIn functionality (Prodromou, 2015). In the absence of academic inquiries, industry research suggests numerous practices to grow the number of LinkedIn followers: (1) attach the platform follow button to the firm website, (2) include the firm LinkedIn page link in all marketing templates, (3) post content daily, (4) check the page activity tab daily, (5) cross promote the firm LinkedIn page on other social media, (6) notify influencers or other pages related to the post, (7) invite personal connections to follow the firm LinkedIn page, (8) use different hashtags based on current goals when posting, (9) review the firm page analytics, and (10) research the firm competitors' content (Lessard, 2019). Moreover, LinkedIn (2020a) states that consistent and compelling firm posting is key to acquiring and retaining followers. However, neither extant B2B literature nor the platform speaks to posts' content and how it can influence customer engagement.

3.3. Brand personality of posting

Brand personality is defined as "the set of human characteristics associated with a brand" (Aaker, 1997, p. 347). Brand personality is relevant in the buyer–seller interaction process as it serves as an efficient way to distinguish a firm from its competitors at the symbolic level (Sung & Kim, 2010). In general, brands can be linked to human personality traits via learning and experience because perceptions of brand personality traits can be shaped and affected by direct or indirect contact that a customer has with the brand (Aaker, 1997). According to Brakus et al. (2009), a brand's personality may be inferred from product attributes, people associated with the brand (e.g., company personnel), or general communications. We consider that this idea can be extended to a digital setting, particularly to the LinkedIn posts of B2B service firms. In this vein, customers may differently engage with a firm due to the observed posts' brand personality diverging from their own personality. This is consistent with previous research noting that the personality of a brand enables the customers to communicate their personality, desired self-expressions, or specific dimensions of the projected self (Sung & Kim, 2010).

We follow the brand personality framework suggested by Aaker (1997). This conceptual framework entails five dimensions: (1) sincerity (composed of down-to-earth, honest, wholesome, and cheerful traits), (2) excitement (composed of daring, spirited, imaginative, and up-to-date traits), (3) competence (composed of reliable, intelligent, and successful traits), (4) sophistication (composed of upper class and charming traits), and (5) ruggedness (composed of outdoorsy and tough traits). Even though personality traits associated with a brand tend to be relatively enduring and distinct (Aaker, 1997), the components of a LinkedIn post are highly dynamic because the text, image/video, appeals, and design elements can evolve through time and be specific to a certain type of content. For instance, while a post about visiting a mining customer site in a remote location may be dominantly perceived as "outdoorsy," a post about the health of managers involved in an industrial accident may be dominantly perceived as "honest." Therefore, the diversity in the regular operations of a B2B service SME provides enough variability for content generation, thereby lending support to our data being the right fit for this study. In light of Aaker's framework being comprehensive but having a penta-factorial structure that allows variance in the trait relevance according to the context (Herbst & Merz, 2011), investigating the elasticities of posts' brand personality dimensions associated to customer engagement behaviors is a fruitful research endeavor.

Because prior studies have not explored the LinkedIn platform and only provided sparse insights into the customer engagement behaviors and type of content in social media (Dessart, 2017; Agnihotri, 2020), it is difficult to form expectations beforehand. Hence, we abstain from developing hypotheses (De Vries, Gensler, & Leeflang, 2017). Rather, we focus on answering the research questions by shedding light on the relative effect that size, direction, and persistence of the different posts' brand personality dimensions (i.e., sincerity, excitement, competence, sophistication, and ruggedness) have on customer engagement (i.e., exposure, perceptions, and actions) and the interrelationships among all the theorized LinkedIn posting elements (see Fig. 1).

4. Method

4.1. Research setting

We use LinkedIn data on customer engagement from a Chilean-Swiss consultancy firm operating in two countries where it provides marketing and sales consulting, market research, and training services for B2B companies (focusing on large-sized suppliers). At the beginning of the study (2018), the focal firm had about two years' experience in its main geographic markets. The focal firm is one of four specialized (B2B) consultancy providers in the target markets. Young B2B organizations tend to focus on digital communication due to their comfort with online

[2] Using the LinkedIn app, the user needs to click on the name or logo in the post and then click on the follow button.

technologies and limited access to resources (Ghekiere & Zinkevich, 2019). A common goal for nascent firms is to achieve customer engagement[3] on social media (Chang et al., 2019) because financial metrics like profitability are not yet applicable (Winkler, Rieger, & Engelen, 2020). The importance of social media and digital communications for firms operating in the B2B space was further highlighted by the findings of a survey we conducted with a sample (N = 125) of prospects and current customers of the focal firm. Approximately 87% of the target executives had a LinkedIn account and, among them, the average agreement with the statement "I use LinkedIn daily" was 9.1 (on a scale of 1–10). Moreover, young firms tend to have few formal rules and little inertia (Winkler et al., 2020), enabling a more flexible approach to posting (i.e., more variability in brand personality dimensions). Hence, the focal B2B SME provides a useful setting for this research. The longitudinal data span 114 weeks during the 2018–2020 period.

4.2. Data

For our study, we consider *perceived sincerity of LinkedIn posts, perceived excitement of LinkedIn posts, perceived competence of LinkedIn posts, perceived sophistication of LinkedIn posts, perceived ruggedness of LinkedIn posts*, *number of impressions, number of likes, number of clicks, number of shares, number of comments,* and *number of new followers* (all measured at the weekly level) as endogenous variables.

Brand personality. The posts shared by the B2B firm on its LinkedIn page show traits of brand personality emerging from the content and graphic design of the posts. Five independent coders (customers of the focal firm) analyzed the content data of 211 posts published in the research timeframe, based on Aaker's (1997) brand personality framework. Using a 5-point scale (1 = not at all descriptive and 5 = totally descriptive), coders were asked to rate the extent to which each post described the brand personality traits (of each dimension). This rating scheme allowed the coders to associate more than one brand personality dimension with each post, if they considered it appropriate. The coders used the traits informed by the brand personality framework (Aaker, 1997, p. 352) to conceptualize the dimensions. We conducted exploratory factor analysis to identify whether the coders used the same criterion. Four coders (out of five) accurately (i.e., based on validity of the measurement) assessed the posts (all factor loading greater than 0.5). The Cronbach's alpha (0.76) and composite reliability (0.81) values exceeded the 0.7 minimum cutoffs, respectively, thereby establishing consistency of the measurement. Next, we averaged the four coders' (after dropping the ratings from one coder whose assessment was found to be faulty) brand personality scores (per dimension). Finally, the scores of the posts' brand personality dimensions were averaged at the weekly level (if no post was published in a week, the brand personality dimensions took a zero value). Out of the 114 weeks, we had 16 (14.0%) weeks with no posts in our data.

Exposure. This is operationalized using impressions, i.e., how many times a post was seen by users on LinkedIn and can potentially affect perceptions and actions (new follower count) towards the firm. It can also affect the brand personality of posts via feedback effects, i.e., higher (lower) impressions for posts expressing a certain type of brand personality may influence the firm to subsequently include more (less) of such type of posts on their account. Like other variables in our model, impressions were also aggregated for all posts at the weekly level.

Perceptions. For each week in the period of observation, we computed the total number of likes (including celebrate, support, love, insightful, and curious), which is deemed as direct performance of posts (Chang et al., 2019). We also computed the number of clicks, shares, and comments at the weekly level. These variables were operationalized independently since they can represent manifestations of different types of perceptions (Larsson, 2018).

Actions. We aggregated the daily number of new followers of the firm's LinkedIn profile at the weekly level. On LinkedIn, followers are obtained either organically or through sponsored activities. Since the focal firm had not invested in acquiring followers through paid activities before or at the time of data collection, we only observe organically acquired followers in our data, which probably are the most interesting set of followers.

Control variables. We control for other factors that could affect the endogenous variables. Namely, we control for wins, events, sales calls, emails, and website visits, which we obtain from a weekly sales report created by the focal firm. Further, we also control for LinkedIn page visits (obtained from LinkedIn profile data available to the focal firm), and general interest regarding the service category in which the focal firm operates. We obtain the general interest related to the service category of the focal firm from Google Trends by averaging the interest for the service category in both the countries where the focal firm operates. Additionally, we also include an indicator for whether an observation occurred before or during the COVID-19 pandemic because this catastrophic situation can affect social exchange and customer engagement in B2B settings (Mora Cortez & Johnston, 2020).

Wins are total accepted quotes (in €) of the company at the weekly level. The date of the win is defined as the day on which a purchase order was generated by the customer, or, if a customer did not use a purchase order, then either a formal email or letter confirmation was sent. It accounts for the financial performance of the focal firm. *Events* are all points of contact with groups of managers (considering the focal firm's target market) such as trade shows, seminars, summits, etc. These activities are organized either by the focal firm or by others. These events present opportunities to network with decision-makers from different firms and are a potential source of influence on customer engagement behaviors on LinkedIn. *Sales calls* are buyer–seller telephone interactions initiated by the seller to inform about its services. *Emails* are communication via email initiated by the seller to inform about its services. *Website visits* could be a signal of interest in the firm's services and can positively affect the firm's LinkedIn experience. We compute this variable as the total number of weekly visits to the focal firm's website. *LinkedIn page visits* are the number of visits the LinkedIn page of the focal firm received at the weekly level. We did not consider the number of LinkedIn page visits as an endogenous variable because clicks are the main source of reaching the landing page in the platform (Prodromou, 2015). Thus, it pertains to customers reaching the LinkedIn page of the focal firm emerging from a different driver than experiencing a post. *Google search* is the market-initiated query for the focal firm's main service category on Google (provided by Google Trends). It captures organic market interest in competitors and substitutes. This variable was selected because not enough data were available using each of the competitors' names.

4.3. Model specification

In this study, we are interested in the effects of posts' brand personality and customer engagement behaviors over time, including the interrelations between them. Thus, to account for the complex interrelations between the variables we use a VAR model with exogenous variables (VARX). To accurately compare the effectiveness of the endogenous variables, we compute their cumulative elasticities over time by using impulse response functions (IRFs). We begin by conducting the Granger causality test to determine whether *Sincerity*, *Excitement*, *Competence*, *Sophistication*, *Ruggedness*, *Likes*, *Clicks*, *Shares*, *Comments*, and *New Followers* are actually endogenous. Given our data is weekly, we use up to four lags in the test and report the lowest *p*-values in Table 2 (e.g., De Vries et al., 2017). The results show that 75 (68.2%)

[3] We randomly selected 10 weeks from our data and manually classified the source of engagement. During an average week about 80% of observable engagement behavior with the focal firm came from current and potential customers of the firm.

Table 2
Results of granger causality tests.

Dependent Variables (DV)											
DV Granger-caused by…	**New Followers**	**Impressions**	**Likes**	**Clicks**	**Shares**	**Comments**	**Sincerity**	**Excitement**	**Competence**	**Sophistication**	**Ruggedness**
New Followers	–	0.008	0.058	0.058	0.010	0.023	n.s.	0.066	n.s.	0.037	0.054
Impressions	0.057	–	n.s.	0.083	n.s.	0.041	n.s.	n.s.	n.s.	n.s.	n.s.
Likes	n.s.	0.047	–	0.013	0.007	0.012	0.043	0.005	0.005	0.011	0.043
Clicks	0.049	0.012	0.067	–	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
Shares	0.075	n.s.	n.s.	0.078	–	0.093	0.020	0.013	0.030	0.039	0.038
Comments	n.s.	n.s.	0.055	0.067	0.081	–	n.s.	n.s.	0.071	0.081	n.s.
Sincerity	0.017	0.034	0.081	n.s.	n.s.	0.077	–	0.060	0.071	n.s.	0.096
Excitement	0.025	0.030	0.072	0.079	0.018	0.062	0.061	–	0.062	0.083	0.037
Competence	0.019	0.037	0.071	n.s.	0.071	0.057	n.s.	0.068	–	n.s.	0.029
Sophistication	0.039	0.030	0.065	0.081	0.078	0.084	n.s.	0.072	n.s.	–	n.s.
Ruggedness	0.021	0.025	0.063	0.081	n.s.	n.s.	0.088	0.034	0.057	0.056	–

Note: n.s. = not significant ($p > .10$). Minimum p-values across six lags.

out of the 110 effects are significant at the $\alpha = 0.10$ level, providing evidence of Granger causality among an adequate number of variables (see Table 2).

Next, we use the Phillips-Perron (PP) test to evaluate the stationarity of our time series (Pauwels, 2004). Since we include constant terms (α) and deterministic time trends (δ_t) in our model to capture the effects of omitted, gradually changing variables, the popular Dickey-Fuller test is less appropriate due to low power in such cases (e.g., Enders, 2004). Hence, we use the PP test which is known to perform better than the Dickey-Fuller test in the given context (Pauwels, 2004; De Vries et al., 2017). As shown in Table 3, the PP test is significant for all metric variables, thereby providing evidence of stationarity for the variables.

Similar to previous studies that explore the interrelationships between marketing variables in the digital context and performance metrics (e.g., De Vries et al., 2017), we use a double logarithmic (ln-ln) transformation on all continuous variables in the model. Before applying the log transformation, we added a small positive constant (+1) to all continuous variables in the model that could theoretically take a value of zero. We specify the VARX model for the LinkedIn experience in Equation (1), where the vector of endogenous variables: impressions (Impressions), likes (Likes), clicks (Clicks), shares (Shares), and comments (Comments), number of new followers (New_Fol) on LinkedIn, and perceived sincerity (Sincerity), excitement (Excitement), sophistication (Sophistication), and ruggedness (Ruggedness) of post personality, is explained by its own lagged values, accounting for the dynamic interrelations between the variables. To account for omitted variables that can evolve over time, we included a constant term (α) and a deterministic time trend (δ_t) for all endogenous variables (Pauwels, 2004).

Table 3
Unit root test results (PP test).

Variables	PP Test Statistic	Stationary?
New Followers	−6.16*	Yes
Impressions	−6.16*	Yes
Likes	−5.67*	Yes
Clicks	−6.48*	Yes
Shares	−7.58*	Yes
Comments	−8.40*	Yes
Search Interest	−9.47*	Yes
Sincerity	−8.62*	Yes
Excitement	−8.73*	Yes
Competence	−8.64*	Yes
Sophistication	−8.76*	Yes
Ruggedness	−8.57*	Yes
LinkedIn Page Visits	−6.17*	Yes
Wins	−8.44*	Yes
Website Visits	−4.19*	Yes
Number of Posts	−7.68*	Yes

* $p < .05$. Note: H_0: The series contains a unit root (i.e., non-stationary). All variables are ln-transformed.

Additionally, we control for average weekly Google search interest in the main service category (GSearch; 0-100) in which the focal firm operates, N_{posts} (the number of weekly posts published by the focal firm), Events (1 if at least one event takes place during the week, 0 otherwise), sales calls (Sales_Call; 1 if any sales calls were made to potential and existing customers during the week, 0 otherwise), emails (Email; 1 if emails were sent to potential and existing customers during the week, 0 otherwise), Webs_Visits (the number of weekly visits to the focal firm website), LinkedIn_Pg_Visits (the number of weekly visits to the focal firm LinkedIn page), Wins (the number of weekly closed deals in €), and whether the week of observation was during or before the COVID-19 pandemic (Covid; 1 if week lies in the pandemic period, 0 otherwise). Descriptive statistics and detrended correlations are reported in Web Appendix C and D.

$$\begin{bmatrix} \ln(New\_Fol_t) \\ \ln(Impressions_t) \\ \ln(Likes_t) \\ \ln(Comments_t) \\ \ln(Shares_t) \\ \ln(Clicks_t) \\ \ln(Sincerity_t) \\ \ln(Excitement_t) \\ \ln(Competence_t) \\ \ln(Sophistication_t) \\ \ln(Ruggedness_t) \end{bmatrix} = \begin{bmatrix} \alpha_{New\_Fol} \\ \alpha_{Impressions} \\ \alpha_{Likes} \\ \alpha_{Comments} \\ \alpha_{Shares} \\ \alpha_{Clicks} \\ \alpha_{Sincerity} \\ \alpha_{Excitement} \\ \alpha_{Competence} \\ \alpha_{Sophistication} \\ \alpha_{Ruggedness} \end{bmatrix} + \begin{bmatrix} \delta_{t,New\_Fol} \\ \delta_{t,Impressions} \\ \delta_{t,Likes} \\ \delta_{t,Comments} \\ \delta_{t,Shares} \\ \delta_{t,Clicks} \\ \delta_{t,Sincerity} \\ \delta_{t,Excitement} \\ \delta_{t,Competence} \\ \delta_{t,Sophistication} \\ \delta_{t,Ruggedness} \end{bmatrix} + \begin{bmatrix} \theta_{1,1} & \cdots & \theta_{1,4} \\ \vdots & \ddots & \vdots \\ \theta_{11,1} & \cdots & \theta_{11,4} \end{bmatrix}$$

$$\times \begin{bmatrix} X_{1,t} \\ X_{2,t} \\ X_{3,t} \\ X_{4,t} \end{bmatrix} + \begin{bmatrix} \beta_{1,1} & \beta_{1,5} \\ \vdots & \vdots \\ \beta_{11,1} & \beta_{11,5} \end{bmatrix}$$

$$\times \begin{bmatrix} ln(Web\_Visits_t) \\ \ln(GSearch_t) \\ \ln(Wins_t) \\ \ln(N_{Posts\,t}) \\ \ln(LinkedIn\_Pg\_Visits_t) \end{bmatrix}$$

$$+\sum_{j=1}^{J}\begin{bmatrix}\Phi^{j}_{1,1} & \cdots & \Phi^{j}_{1,11}\\ \vdots & \ddots & \vdots\\ \Phi^{j}_{11,1} & \cdots & \Phi^{j}_{11,11}\end{bmatrix}\times\begin{bmatrix}\ln(New\_Fol_{t-j})\\ \ln(Impressions_{t-j})\\ \ln(Likes_{t-j})\\ \ln(Comments_{t-j})\\ \ln(Shares_{t-j})\\ \ln(Clicks_{t-j})\\ \ln(Sincerity_{t-j})\\ \ln(Excitement_{t-j})\\ \ln(Competence_{t-j})\\ \ln(Sophistication_{t-j})\\ \ln(Ruggedness_{t-j})\end{bmatrix}+\begin{bmatrix}\varepsilon_{t,New\_Fol}\\ \varepsilon_{t,Impressions}\\ \varepsilon_{t,Likes}\\ \varepsilon_{t,Comments}\\ \varepsilon_{t,Shares}\\ \varepsilon_{t,Clicks}\\ \varepsilon_{t,Sincerity}\\ \varepsilon_{t,Excitement}\\ \varepsilon_{t,Competence}\\ \varepsilon_{t,Sophistication}\\ \varepsilon_{t,Ruggedness}\end{bmatrix} \quad (1)$$

where t indicates the unit of time (week), j indicates the number of lags and J indicates the maximum number of lags chosen for the model. X_i s are exogenous dummy variables (Email, Sales_Call, Covid, and Events) and Θ is the matrix of its parameters. B is the matrix of parameters for the exogenous metric variables Web_Visits, Wins, LinkedIn_Pg_Visits, N_{posts} and GSearch and $\Phi^{j}_{i,i}$ are parameters of the lagged endogenous variables representing direct and indirect effects among the endogenous variables. Finally, the error terms of each endogenous variables are represented by ε_t.

We use the Schwarz information criterion (SC), Final Predictor Error (FPE), and Hannan-Quinn information (HQ) criterion to conclude that the number of lags for the endogenous variables in the VARX model is one (see Web Appendix E). We test the assumption that there is no autocorrelation between the residuals of the VARX model using the Lagrange autocorrelation test. We compute the wild bootstrapped (WB) *p*-values to account for conditional heteroscedasticity in the error terms. This approach is recommended for relatively small samples (T ≈ 100; Ahlgren & Catani, 2017). In line with Vieira et al. (2019), we conduct the test up to the 5th lag and, for each lag, the test indicates no autocorrelation among the residuals (see Web Appendix F).

5. Findings

Following prior research (e.g., De Vries et al., 2017), we examine effects between the endogenous variables through generalized impulse response functions (IRFs). We obtain 121 IRFs for the response of 11 endogenous variables to shocks, applied in turn to each variable (Hewett et al., 2016). The IRFs inform mean responses and 90% confidence intervals to assess the significance of such responses. Drawing on the IRFs, we compute the cumulative elasticities[4] (accumulation of significant effects). This way, we can contrast the effects across posts' brand personality (sincerity, excitement, competence, sophistication, and ruggedness), exposure (impressions), perceptions (likes, clicks, shares, and comments), and actions (new followers).

5.1. Posts' brand personality influence on customer engagement behaviors

As Table 5 indicates, posts' excitement is fruitful in building customer engagement in LinkedIn because it creates impressions (0.173) and likes (0.079), meaning that a 1% increase in customers' perceived level of posts' excitement leads to a 0.173% increase in impressions and a 0.079% increase in likes, respectively. An explanation for the former effect might be that exciting posts generate a subconscious energy rush in the customers – who generally scroll down through their feed quickly – resulting in greater visual attention on the posts (Wyka, 2019). It is important to mention that social media users receive an endless flow of information, often at a rate far higher than their cognitive abilities to process information (Rodriguez, Gummadi, & Schoelkopf, 2014). An explanation for the latter effect might be that customers perceiving a post as exciting affects their mood positively and they reciprocate by liking the post. In addition, this is consistent with previous research showing that managers in a positive mood disclose more information about themselves (Forgas, 2011), considering that liking a post is a public action on the platform. We also observe that the effect of posts' excitement lasts longer for impressions than for likes (weeks 0–1 vs. week 2, respectively). The temporal aspect of these effects shows initial evidence of the causal chain relating impressions to likes.

Two other brand personality dimensions have a significant influence on customer engagement behaviors. On one hand, customers' perceived level of a post's competence affects clicks significantly. A 1% increase in a post's competence leads to a 0.131% increase in clicks (week 1). The reason might be that a post's competence drives the credibility of the post, which, in turn, enhances the willingness to further explore the content and information source by clicking either on the post or the firm name/logo, respectively. This engagement mechanism is supported in extant literature referring to managers assessing the credibility of the information source before establishing further interaction (Westerman, Spence, & Van Der Heide, 2014). On the other hand, a customer's perceived level of posts' ruggedness affects the number of new followers; a 1% increase in posts' ruggedness leads to a 0.324% increase in new followers (weeks 0–1). A possible explanation might be that customers want to work with service firms experienced in their markets who are driven and strong enough to be in the field. These characteristics may be inferred through "outdoorsy" and "tough" personality traits in a post. We highlight the stipulation that an industrial site is dangerous (e.g., heavy machinery operation; hazardous chemicals handling) and relatively uncomfortable (e.g., a fish processing plant is smelly; a steel mill is very hot; a shipping port is overwhelming; a poultry farm is noisy) in comparison with a retail/consumer operation (e.g., bank, grocery store).

Remarkably, both sincerity and sophistication brand personalities are not associated with customer engagement behaviors. The former null effect can be explained by two simultaneous forces linked to sincerity: (A) implying high moral values and idealistic purposes that may increase customers favorability, and (B) manifesting that an offering is not perfect or even possesses weaknesses that may destroy value for customers. The latter null effect can be explained by two simultaneous forces linked to sophistication: (A) indicating high class, exclusiveness or elegancy that may drive the customer's feeling of uniqueness, and (B) insinuating that an offering can be posited as expensive not necessarily due to functionality, harming the customer's value-in-use perception.

5.2. Interrelationships among customer engagement behaviors

We examine how impressions, likes, clicks, shares, comments, and followers affect one another (Table 4). We find that a 1% increase in impressions leads to 0.581%, 0.896%, and 0.063% increases in likes (weeks 0–2), clicks (weeks 0–3), and shares (week 0), respectively. These results suggest that impressions play a key role in building up further customer engagement in social media. In practice, there is no chance for a customer to like, share, or click on a post without looking at the post first (i.e., generating an impression). However, more thoughtful explanations can also be provided. Regarding the association between impressions and likes, a potential reason for this effect might be that the content of posts matches the expectations of customers, satisfying them and enhancing their social belonging (Chang et al., 2019), which, in turn, trigger a reaction in the form of a like. Regarding the association between impressions and shares, a possible reason might be that looking at a post may motivate networking behaviors (e.g., socializing, sharing) to satisfy psychological needs (e.g., relationship), because individuals

[4] We also ran the analysis after dropping the 16 weeks which had 0 posts from our data. The substantive results remain the same.

Table 4
Cumulative elasticities of the endogenous variables.

Impulses in …															
Responses of …	**Excitement**			**Competence**			**Ruggedness**			**Sincerity**			**Sophistication**		
	Elasticity	Wear-in	Wear-out	Elasticity	Wear-in	Wear-out	Elasticity	Wear-in	Wear-out	Elasticity	Wear-in	Wear-out	Elasticity	Wear-in	Wear-out
Impressions	0.173	0	2	–	–	–	–	–	–	–	–	–	–	–	–
Likes	0.079	2	3	–	–	–	–	–	–	–	–	–	–	–	–
Clicks	–	–	–	0.131	1	2	–	–	–	–	–	–	–	–	–
Shares	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Comments	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Followers	–	–	–	–	–	–	0.324	0	2	–	–	–	–	–	–

Impulses in …												
Responses of …	**Impressions**			**Likes**			**Clicks**			**Followers**		
	Elasticity	Wear-in	Wear-out	Elasticity	Wear-in	Wear-out	Elasticity	Wear-in	Wear-out	Elasticity	Wear-in	Wear-out
Impressions				–	–	–	–	–	–	0.115	1	2
Likes	0.581	0	3				–	–	–	–	–	–
Clicks	0.896	0	4	–	–	–				–	–	–
Shares	0.063	0	1	0.128	0	1	–	–	–	–	–	–
Comments	–	–	–	0.171	0	1	0.138	0	1	–	–	–
Followers	–	–	–	–	–	–	0.131	0	1			

Note: Dashes indicate non-significant effects; empty cells indicate own effects (not examined). Wear-in indicates the week in which the effect starts. Wear-out indicates the week in which the effect culminates. Impulses in shares and comments do not generate significant responses for 90% confidence intervals.

Table 5
Parameter estimates of the VARX model.

	Ln (Impressions)	Ln(Likes)	Ln (Clicks)	Ln(Shares)	Ln (Comments)	Ln (New Followers)
Ln(Impressions)$_{(t-1)}$	0.539	0.236	0.212*	0.102	0.074	−0.030
Ln(Likes)$_{(t-1)}$	−0.341	0.034	0.223	0.124	0.209	0.061
Ln(Clicks)$_{(t-1)}$	0.040	−0.029	0.056	−0.127	0.195	0.007
Ln(Shares)$_{(t-1)}$	−0.216	−0.041	−0.246	0.096	−0.031	0.069
Ln(Comments)$_{(t-1)}$	0.053	0.002	0.036	0.125	0.031	0.134
Ln(Followers)$_{(t-1)}$	0.156	0.077	0.089	−0.009	0.033	0.057
Ln(Sincerity)$_{(t-1)}$	−1.688	0.617	−1.945	1.652	−1.379	2.202
Ln(Excitement)$_{(t-1)}$	2.145*	1.951*	−2.122	0.045	0.167	−3.079*
Ln(Competence)$_{(t-1)}$	0.592	−2.197	2.775*	−1.048	1.366	−2.043
Ln(Sophistication)$_{(t-1)}$	1.023	0.343	−0.621	−0.482	−0.245	−1.038
Ln(Ruggedness)$_{(t-1)}$	−1.412	−0.757	1.369	−0.360	−0.094	4.186**
Constant	0.253	−2.047**	−1.289	−1.087*	−0.859	−1.032*
Trend	−0.004	0.006	−0.009	0.005	−0.001	0.011**
Revenue	−0.035	−0.012	0.002	−0.011	−0.004	0.022
Website_visits	0.535**	0.342	0.919**	0.181	0.255	0.384*
LinkedIn_pg_visitors	0.027	0.112	0.078	0.152*	0.013	0.346**
Events (dummy)	0.217	−0.073	0.175	−0.079	−0.047	0.039
Email (dummy)	−0.084	−0.140	−0.252	−0.263*	0.029	−0.055
Sales_call (dummy)	−0.324	−0.181	−0.545*	−0.026	−0.058	0.095
Covid (dummy)	−0.112	−0.555*	−0.145	−0.107	0.163	0.641**
Google_search	−0.100*	−0.029	−0.120*	−0.046	−0.050	−0.029
N_posts	1.561**	1.640**	1.228**	0.344**	0.457*	−0.141
R-square	0.747	0.816	0.730	0.389	0.284	0.775

* $p < .10$.
** $p < .05$.

are designed to pursue relational connection in social groups (Wakefield & Wakefield, 2016). Regarding the association between impressions and clicks, an explanation for this effect might be that looking at the post drives managers' curiosity, which, in turn, leads to accruement of knowledge (Lydon-Staley, Zurn, & Bassett, 2020). This may be achieved by clicking on the post to further examine its content or clicking on the firm name/logo to learn about the firm. Interestingly, the effect of impressions lasts longer than any other engagement behavior. The latter sheds light on B2B customers processing information more rationally and less impulsively (Lilien, 2016), even in online environments.

Furthermore, we find that likes are effective in creating more shares and comments. A 1% increase in likes leads to 0.128% and 0.171% increases in shares (week 0) and comments (week 0), respectively. A potential reason might be that B2B customers perceive likes as brand endorsements (Chang et al., 2019), increasing the trust in the content, which, in turn provides confidence to the customer to further engage in the platform. These results are consistent with previous research on social media, which considers likes a more basic type of engagement but highly influential on sharing and commenting (see Larsson, 2018, p. 334). Moreover, we find that clicks significantly affect comments and new followers. A 1% increase in clicks leads to 0.138% and 0.131% increases in comments (week 0) and followers (week 0), respectively. The former effect can be explained by customers processing the clicked information and elaborating a question or remark in the form of text on the post thread. During an ex-post review of the posts in the sample, we observed that many of the comments were associated with inquiries asking the focal firm to provide more information on their activities or tagging colleagues who could be interested in the content. The latter

effect can be explained by customers processing the clicked information and concluding that the content is relevant for their professional development, thereby deciding to become a follower (Diba et al., 2019).

Finally, we find that the number of new followers influences the number of impressions; a 1% increase in new followers leads to a 0.115% increase in impressions during week 1 (i.e., t + 1). The reason might be that amplifying the number of followers increases the reach of new posts, which, in turn, leads to more impressions. The temporality of the effect (week 1) supports this explanation as the influence of clicks on new followers is realized during week 0 and the influence of ruggedness on new followers is realized during weeks 0–1. Hence, there is a benign cycle starting with impressions, which leads to more clicks, which, in turn, leads to new followers, which consequently leads to more impressions. In other words, by continuously posting content that enables customers to create impressions and clicks in week 0, a firm can increase the number of followers, to finally derive more impressions during the next week. In addition, the perpetuity of the described cycle depends on the brand personality of the content as *excitement* drives impressions, *competence* drives clicks, and *ruggedness* drives new followers (see Table 4).

5.3. Feedback effects and control variables

We find support for some feedback effects and discuss them accordingly. Improvements in the number of impressions lead to higher evaluations of all brand personality dimensions; a 1% increase in impressions leads to 0.116%, 0.097%, 0.102%, 0.101%, and 0.098% increases in perceived sincerity, excitement, competence, sophistication, and ruggedness, respectively, during week 0. In addition, the number of likes positively influences the evaluations of all brand personality dimensions; a 1% increase in likes leads to 0.125%, 0.115%, 0.126%, 0.118%, and 0.118% increases in perceived sincerity, excitement, competence, sophistication, and ruggedness, respectively, during week 0. These results indicate that the focal firm can monitor impressions and likes in real-time and, consequently, create new posts in the same week with features from previous posts that received higher engagement (i.e., more elements of desirable brand personality dimensions).

We next discuss some of the noteworthy findings from the exogenous parameters (see Table 5). The number of posts per week has a positive and significant effect on all customer engagement behaviors ($\beta_{n\_post} \rightarrow_{impressions} = 1.561$, $\beta_{n\_post} \rightarrow_{likes} = 1.640$, $\beta_{n\_post} \rightarrow_{clicks} = 1.228$, $\beta_{n\_post} \rightarrow_{comments} = 0.457$, $\beta_{n\_post} \rightarrow_{shares} = 0.344$, $ps < 0.10$), except new followers ($\beta_{n\_post} \rightarrow_{followers} = -0.141$, $p = .43$). In the current dataset, the number of weekly posts fluctuates from 0 to 5, with no posts on weekends. Hence, posting daily is an effective way to drive customer engagement behaviors. In this vein, the platform suggests posting one to two times per day, arguing that this practice allows firms to establish a trusted voice within their community (see LinkedIn, 2020a). The deterministic trend is significant and positive for new followers ($\delta = 0.011$, $p < .05$), indicating that the number of followers slightly increases over time. The number of website visits affect impressions ($\beta = 0.582$) as well as likes ($\beta = 0.342$), clicks ($\beta = 0.919$), and new followers ($\beta = 0.384$) significantly and positively ($ps < 0.05$). A potential explanation is that the focal firm's website serves as a content validation source, which seems to be evaluated favorably by customers. Similarly, the number of LinkedIn page visitors is positively related to shares and new followers ($\beta = 0.152$, $\beta = 0.346$, respectively; $ps < 0.10$). Hence, the focal firm's LinkedIn page describes itself adequately to the customers, which enhances the firm's merit and validates its content (Ghekiere & Zinkevich, 2019). The sales call dummy affects clicks significantly and negatively ($\theta = -0.545$, $p < .05$). This effect could be caused by the fact that a verbal conversation with a representative is effective enough to demotivate the customer from scrutinizing the focal firm's LinkedIn posts. The emails dummy negatively affects the number of shares ($\theta = -0.263$, $p < .10$). This result indicates that customers may have assumed that their network also received the email, discouraging them from sharing the content on LinkedIn. During an ex-post conversation with the focal firm, we confirmed that the content disseminated is consistent across communication channels.

5.4. Robustness checks

We ensured the robustness of our results by performing several additional tests. First, we estimated a linear model by using a weighted least squares (WLS) estimator to account for different variances of the error terms in the multiple equations. The WLS approach allows data points not to be treated uniformly, cross-sectionally corresponding to the longitudinal nature of the dataset. We specified the WLS model using a lag equal to 1 for all the endogenous variables. The findings and the explanatory power of the WLS model are similar to the VARX model (see Web Appendix G). However, the theorized VARX model is generalizable, fits the conceptual framework better, and enables capturing the complex interrelations among posts' brand personality, exposure, perceptions, and actions over time (Vieira et al., 2019).

Second, we estimated a reduced VARX model to examine whether the posts' brand personality dimensions metrics might be prone to measurement error (De Vries et al., 2017). Measurement error could lead to inconsistency or upward bias in parameter estimates (e.g., Wooldridge, 2016). We removed the posts' brand personality dimensions metrics, *ceteris paribus*. Model fit of the reduced specification is lower than that of the full model ($\Delta AIC = 24.953$; $\Delta SC = 21.083$), supporting the contribution of the brand personality dimensions in the modeling. We computed the cumulative elasticities of the interrelations among the customer engagement behaviors (Web Appendix H). A 1% increase in impressions leads to 0.581%, 0.813%, and 0.065% increases in likes, clicks, and shares, respectively (full model: 0.581%, 0.896%, and 0.063%, respectively). A 1% increase in likes leads to 0.166% and 0.130% increases in comments and shares, respectively (full model: 0.128% and 0.171%, respectively). A 1% increase in clicks leads to 0.161% and 0.139% increases in comments and new followers, respectively (full model: 0.138% and 0.131%, respectively). A 1% increase in new followers leads to a 0.116% increase in impressions (full model: 0.115%). The only substantial result differing from the full model is the cumulative elasticity associated with the effect of comments on new followers (0.109%) during week 1. We checked the full model and identified that this cumulative effect (0.099%) is also significant when using an 85% confidence interval.

As a final robustness check, we estimated a VARX model considering a new brand personality approach suggested by Herbst and Merz (2011) for industrial settings, which conceptualizes brand personality via three factors (performance, sensation, and credibility; see the specifying traits in p. 1078, Herbst & Merz, 2011) instead of five. The brand personality dimensions were coded by the same four customers following the procedure described in the method section, showing adequate psychometric properties. The new model fits the data worse than the original model ($\Delta AIC = 13.874$; $\Delta SC = 12.186$). However, most of the substantive findings related to customer engagement behaviors do not change (see Web Appendix I). A 1% increase in impressions leads to 0.580%, 0.901%, and 0.064% increases in likes, clicks, and shares, respectively (full model: 0.581%, 0.896%, and 0.063%, respectively). A 1% increase in likes leads to 0.143% and 0.136% increases in comments and shares, respectively (full model: 0.128% and 0.171%, respectively). A 1% increase in clicks leads to 0.140% and 0.111% increases in comments and new followers, respectively (full model: 0.138% and 0.131%, respectively). A 1% increase in comments leads to a 0.126% increase in new followers (full model: 0.099%, significant at an 85% confidence interval). A 1% increase in new followers leads to a 0.104% increase in impressions (full model: 0.115%). Regarding the new brand personality dimensions, only performance and sensation have a significant influence on customer engagement behaviors (Web Appendix I). A 1% increase in performance leads to a 0.202% increase in new followers and a 0.171% decrease in comments (week 0); and a 1% increase in sensation leads to a

0.119% increase in comments (week 0). Comparatively, the comprehensive Aaker's brand personality framework seems to be more appropriate to conduct a thorough analysis of B2B posting on LinkedIn at the granular level.[5] All in all, the alternative modeling approaches and specifications show the robustness of our findings.

6. General discussion

A key driver of today's marketplace rapid transformation resides in the rise and spread of social media platforms offering new opportunities to interact with customers. Social media afford unique paths to engage customers on deep and meaningful levels (Dessart, 2017). Enabling and sustaining customer engagement through social media marketing represents a vital endeavor to secure sales (Agnihotri, 2020). Hence, B2B firms have focused on such digital platforms because a modern customer follows a purchase-consumption circular loop, which is highly influenced by information in the digital space (Vieira et al., 2019; Ancillai et al., 2019). This study, set in a SME B2B service setting, examines the relative impact of posts' brand personality (sincerity, excitement, competence, sophistication, ruggedness) on different types of customer engagement behaviors (exposure, perceptions, and actions) and their interrelations in LinkedIn. A unique longitudinal dataset adds rigor as prior research argues over the significance of in-depth understanding of social media functionality while considering the time-varying essence of customer engagement behaviors (Meire et al., 2017).

6.1. Theoretical implications

The findings of the study contribute to the B2B SME marketing, social media, and engagement literatures in several ways. First, this study expands the *digital communication* theory (e.g., Hewett et al. 2016; De Vries et al., 2017) by investigating LinkedIn as a particular social media embodying the focal firm's interactive online space. The focal firm utilizes LinkedIn as the only social media channel, which allows for estimating the effectiveness and efficiency of the platform (Salo, 2017) relatively cleanly, and also facilitates better understanding of the underlying mechanisms structuring the LinkedIn experience (Prodromou, 2015). Whereas previous research has tended to focus on isolated aspects of customer engagement behaviors (e.g., likes; Chang et al., 2019), agglomerated customer engagement behaviors (e.g., Vieira et al., 2019), or provided a qualitative analysis of customer engagement behaviors (e.g., Sundström et al., 2020), we consider all possibilities of customer engagement individually (impressions, likes, clicks, shares, comments, becoming a follower) and then theorize and empirically measure their cumulative effect across the LinkedIn experience. We also extend the current view on B2B marketing communication effects by offering a managerial-oriented classification of engagement (exposure, perceptions, and actions). This conceptualization enables researchers to be grounded in practice and better relate to subjects when conducting scholarly endeavors. Moreover, we believe that the suggested conceptualization allows better discrimination of the behavioral options in social media settings.

Second, our findings suggest that impressions are the cornerstone for achieving further customer engagement. The importance of impressions lies in the fact that an unseen post forgoes the chance of receiving a like, click, share, or comment. LinkedIn users spend less time surfing the platform in comparison with Facebook or Twitter users (Patel, 2020). That means there is a good chance that the content that a firm posts on LinkedIn is more likely to be missed simply because users scroll through their feed less. Hence, getting LinkedIn impressions is an achievement in itself. Our findings indicate that a 1% increase in impressions leads to a significant increase in likes, clicks, and shares. By presenting content that helps customers solve a professional problem and move forward in their purchase journey (Rynne, 2017), B2B SMEs can observe manifestations of perceptions (likes, clicks, shares) that signal the effectiveness of the communication messages. The cumulative elasticities for clicks (0.896%) were greater than for likes (0.581%) and shares (0.063%). This result implies that, once the customer's attention is captured, they are nudged to further explore the content, while a more complex mechanism underlies the process of liking and sharing. This is accordant with the descriptive statistics indicating that customers click 137.5 times versus like 20.5 times and share 2.5 times per week. In addition, our findings show that impressions have a persistent effect longer than any other element in the LinkedIn environment, influencing likes from week 0 to week 2 and clicks from week 0 to week 3. This is consistent with the fact that B2B buyers process information meticulously, allowing for prolonged interactions with a brand over time (Ghekiere & Zinkevich, 2019).

Third, our results indicate a cyclical engagement effect emerging from exposure (impressions), passing through perceptions (clicks) to affect actions (new followers), which, in turn, influences exposure. There is limited research that views customer engagement as a process (cf. Viswanathan et al., 2017); therefore, our work advances the engagement literature in a fundamental way. Curiously, likes are not part of the essential mechanism driving the causal network of LinkedIn posting and customer engagement. We believe this finding is interesting for two reasons. First, contrary to the general consensus among previous marketing studies pertaining to the importance of getting more likes in customer-brand interactions (e.g., Chang et al., 2019), our finding suggests that likes are a relatively less important customer engagement behavior. Second, it provides evidence of the B2B customer being more interested in the content of posts (with a click being a vehicle for further post exploration) and their ability to process content in a more rational manner (Lilien, 2016). Furthermore, the association between impressions, clicks, and new followers refutes findings from previous studies that consider content "consumption" as representing a minimum level of engagement (cf. Cao et al., 2021). This finding corresponds to the tendency of B2B customers to remain *barricated* during their evaluation of suppliers as well as to the growing tendency to limit nonformal interaction with suppliers (see Chase & Murtha, 2019). The identified customer *barricaded* behavior might also help explain supposed inconsistencies in prior research, which conclude that social media use does not seem to generally affect customer loyalty (e.g., Bill et al., 2020). Such findings could be attributable to the limitation of cross-sectional survey instruments in grasping intricate thought-procesess, which our longitudinal data are more adept at addressing. We hope these insights will provide critical input for a more grounded discussion of social media in B2B SME marketing.

Fourth, we expand the literature on the branding-social media interface by introducing the brand personality framework (e.g., Aaker, 1997) for social media post assessment. Apart from the general wisdom that brand-related content which contains human characteristics has a positive effect on customer-brand interactions (Eisend & Stokburger-Sauer, 2013), less is known about which personality traits embedded in the brand-related content influence social media customer engagement in B2B markets (Hollebeek, 2019). Our findings show that three brand personality dimensions (excitement, competence, ruggedness) of posts affect the ability of B2B SMEs to increase the number of desired customer engagement behaviors in LinkedIn. An increase in posts' excitement leads to an increase in impressions and likes. This is consistent with prior research arguing that excitement relates to a feeling of being caught up and fascinated, which raises interest in the observant and may provoke behavioral responses (Sung & Kim, 2010). An increase in posts' competence leads to an increase in clicks. This is consistent with previous research indicating that customers in B2B settings react to content resonating with their problem and performance-oriented decision-making (Herbst & Merz, 2011), and consequently

[5] The Aaker's (1997) brand personality dimensions relate to four customer engagement behaviors, while the Herbst and Merz's (2011) brand personality dimensions only relate to two customer engagement behaviors.

may undertake explorative behaviors (Ghekiere & Zinkevich, 2019). Extant literature also indicates that competence relates to a feeling of being secure, which influences purchase behavior (Eisend & Stokburger-Sauer, 2013) of B2B customers (Herbst & Merz, 2011). Thus, a click represents a new, digital manifestation of formal content evaluation. An increase in posts' ruggedness leads to an increase in new followers. This is consistent with prior research showing that ruggedness relates to a feeling of being active and dynamic (Sung & Kim, 2010), which is important for B2B customers due to the commonly hostile operational setting for suppliers. In addition, ruggedness creates the perception of vigor, a key tenet to infer the health of a supplier in order to establish long-term business relationships (Eisend & Stokburger-Sauer, 2013), which is valued by B2B customers (Lilien, 2016). Thus, a perceived "rugged" B2B SME represents a firm with which customers look forward to doing business.

6.2. Managerial implications

Practitioners also acknowledge the relevance of managing LinkedIn as an engagement platform and identifying what type of content to publish as a priority in B2B settings (Bump, 2020). Therefore, generating novel and useful insights is imperative for them. Social media allow customers to co-author the brand story with the firm (Iglesias, Landgraf, Ind, Markovic, & Koporcic, 2020). Thus, social media must be monitored, analyzed, and acted upon. Our study helps B2B marketers in several crucial ways. The most important one might be that managers should internalize the core of LinkedIn engagement as a delta configuration involving: (1) impressions, (2) clicks, and (3) new followers. Focusing on these three metrics could help managers to develop a more grounded social media strategy for LinkedIn. Specifically, the findings of the study suggest a positive association between impressions and clicks, clicks and new followers, and new followers and impressions. In addition, the delta configuration can be further interpreted from a temporal perspective. Impressions have minimal or no commitment to a long-term relationship with the posting firm while clicks have low to medium commitment with the posting firm. New followers have a medium to high commitment to a long-term relationship with the posting firm. In other words, the delta configuration as a whole represents a new manner for establishing buyer–seller relationships. To successfully manage the suggested configuration there are two complementary factors to be considered by B2B marketers. First, managers need to acknowledge that creating impressions, clicks, and new followers are equally important since the chain would be incomplete without any one of them. Second, impressions and clicks are non-observable behaviors on LinkedIn, meaning that the manager is not able to identify who is looking at the posts or clicking on the posts, which unfortunately leads to observing the evolving one-to-one relationship solely at the final stage of the process.

Next, our results suggest that B2B marketers should publish posts with a particular brand personality, stressing the excitement, competence, and ruggedness dimensions. Excitement leads to more impressions and likes, indicating that customer attention is captured by "daring," "spirited," "imaginative," and "up-to-date" traits in the content and graphic design of a post. Thus, interesting, valuable content can be missed by B2B customers if the post is not exciting at first glance. Due to the niche approach of many service SMEs, one possibility is to raise the level of excitement by focusing on the graphic design (i.e., colors, symbols, images, figure-background) instead of the content itself. Competence leads to more clicks, indicating that customers' willingness to explore a post is driven by "reliable," "intelligent," and "successful" traits in the content and graphic design of the post. Thus, B2B customers are prompted to spend more time with a brand where the information is perceived as competent. For example, managers can use citations of academic studies to support claims or discoveries that may be new or relevant for the target audience. Moreover, the competence of a post is better inferred from the content if it is easy to process (Patel, 2020). For instance, a photo of shaking hands due to a purchase agreement can be very effective in showing success to other customers, instead of just writing about it. Ruggedness leads to more new followers, indicating that customers' long-term interest in a firm depends on "outdoorsy" and "tough" traits perceived in the content and graphic design of posts. Hence, B2B customers infer the degree of practical expertise of a supplier from its hands-on or market-oriented communications. For example, firms could inform about the experience of dealing with a technical challenge in the field using a supportive picture or video. In addition, the copy of a post could include slang or terms used in a particular segment as part of their industrial subculture (Mora Cortez & Johnston, 2018).

Finally, our findings indicate that marketing managers in B2B SME settings should consider not only the brand personality of posts but also the number of published posts per week. The LinkedIn algorithm seems to reward firms that post more often than those posting sporadically. The weekly number of posts positively influences the number of impressions, likes, clicks, shares, and comments. Thus, frequency matters. The focal firm published a maximum of five posts per week (from Monday to Friday). Therefore, we cautiously subscribe to the opinion that recommends posting "1–2 times per day" as firms that "post daily get 2x the customer engagement" than firms that do not (LinkedIn 2020a). Our concern comes from the possibility of managers feeling pressured to post more without having meaningful content for their B2B audiences. LinkedIn posting should not be an arbitrary decision; indeed, messages perceived by customers as irrelevant to the purchase hurt customer loyalty (Bill et al., 2020). Hence, we suggest establishing a LinkedIn posting calendar for the next six to 12 months with the main ideas and brand personality dimensions, but allowing some leeway to include new posts based on contemporary events. This plan will provide structure and flexibility to better communicate with customers through LinkedIn. In addition, our research helps marketers to purposely associate the B2B SME website to the LinkedIn account. The number of website visits positively influences the number of impressions, likes, clicks, and new followers, representing favorable complementation. However, sales calls and email campaigns have a negative influence on perceptions (clicks and shares, respectively). Hence, managers need to balance the use of LinkedIn postings, sales calls and emails to customers, due to the identified substitution effects. In this manner, LinkedIn can contribute to reducing the number of sales calls and emails to customers, especially followers, which should result in sustaining the effectiveness of the marketing actions while reducing the costs. For example, reducing the number of calls needed to close a deal from five to four would save a firm $518 (USD) on average (Hill, 2013).

6.3. Limitations and further research

Our study's limitations suggest avenues for future research. First, given the current nature of LinkedIn's proprietary algorithm, our findings are robust and have useful implications for managers. However, further research would be required to ensure the robustness of these results whether LinkedIn introduces major changes to its algorithm. Second, while gathering data only from LinkedIn allows focusing on more granular aspects of digital communication (Hewett et al., 2016) and for the focal firm represents the only social media network used, other B2B SMEs may use several social media networks (e.g., Twitter, Facebook), which can differ in how customer engagement is developed. Future studies should explore such divergences and the potential synergic effects across platforms. Third, our results are based on data that contain information on the LinkedIn communication of a Swiss service firm selling consultancy, market research, and training to B2B firms whose decision-makers (e.g., CMO, CSO) are highly active in social media usage (9.1 out of 10 agreement level regarding: "I use LinkedIn daily"). Further research could investigate customer engagement behaviors with a dataset of more traditional industrial end-users (e.g., construction, mining, pulp and paper, energy). For instance, selling maintenance services for conveyor belts in a mining site involves

interacting with mineral processing superintendents or plant operations managers who have a more technical background than CMOs. Fourth, the focal firm is relatively small in size (<15 full-time employees) and young (est. 2017), which might influence how customers react to digital communication. Future studies could address long-established firms in the market with more than 250 full-time employees and a turnover higher than €50 million.

Fifth, this research purposively adopted a brand personality approach (e.g., Aaker, 1997) to study the published posts of the focal firm because it may be superior to adopting an informative approach (Chang et al., 2019) to account for customer engagement. However, newer theoretical lenses, such as the brand experience concept (Brakus et al., 2009), can be brought to bear in replication studies. Sixth, the feedback and control variable effects discussion is result-driven. Future research could consider a more theoretically grounded analysis to better explain the identified associations. Seventh, while our VARX model took into consideration the Google search of the main service categories to account for competitors' influence, further research might also consider competitive actions more extensively. In our study, the main competitor of the focal firm used LinkedIn actively, but data (using the "companies to track" functionality) on new followers and number of posts were available for only 68 weeks. By testing the extended model, we found that the substantive results remain unchanged. However, further research should study in more depth how the LinkedIn actions of competitors interact with each other. Similarly, this study does not capture the non-digital channels of communication because the focal firm only uses LinkedIn, industry events, sales calls, and emails to interact with customers. Hence, future research may use a dataset entailing offline efforts such as traditional advertising in industry magazines or newspapers. In addition, online customer engagement might be influenced by previous offline efforts such as trade shows, which are an essential component of the B2B marketing communicaiton strategy (e.g., Mora Cortez, Johnston, & Gopalakrishna, 2022). Overall, we hope this study provides an impetus for further research in the engagement-social media domain.

CRediT authorship contribution statement

Roberto Mora Cortez: Conceptualization, Data curation, Writing – original draft, Writing – review & editing, Visualization, Investigation, Validation, Formal analysis, Methodology, Project administration, Software. **Ayan Ghosh Dastidar:** Conceptualization, Data curation, Writing – original draft, Writing – review & editing, Visualization, Investigation, Validation, Formal analysis, Methodology, Project administration, Software.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jbusres.2022.02.086.

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