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Managing the content of LinkedIn posts: Influence on B2B customer engagement and sales?

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ABSTRACT

This study investigates whether LinkedIn content in a business-to-business (B2B) service setting affects how firms generate engagement and sales revenue. Drawing on social media marketing theoretical underpinnings, we explain how a new post typology (sales, technical, and social) and customer engagement (likes, clicks, shares, and comments) are relevant to increase firm performance. We specify a VAR model with exogenous variables (VARX) using 106 weeks of data from a new, steadily growing B2B firm. We focus on the cumulative effects (i.e., short- and long-term effects) of the types of posts, website visits, new followers, and a composite of engagement behaviors over time and compute elasticities with impulse response functions (IRFs). Our findings indicate that followers and website visits positively affect the amount of sales revenue, and sales posts and website visits drive the number of followers. In addition, we find that social posts, new followers, and sales revenue positively influence engagement. These findings demonstrate the utility of LinkedIn at the firm level, preventing top management from perceiving social media as an ornamental accessory, and provide guidance for B2B marketers about what content to post on LinkedIn.

1. Introduction

Business-to-business (B2B) firms are facing sustained growth in social media usage (Jackson, 2018) due to its relatively low cost of implementation, support of sales force activities, and the increasing use of social media by buyers during their purchase journeys (Ancillai, Terho, Cardinali, & Pascucci, 2019; Bill, Feurer, & Klarmann, 2020). Prior B2B research has broadly explored the adoption of social media (e.g., Lacka & Chong, 2016), the use of social media in B2B marketing (e.g., Brennan & Croft, 2012), social media and the selling process (e.g., Agnihotri, Kothandaraman, Kashyap, & Singh, 2012), and social media and marketing strategy (e.g., Keegan & Rowley, 2017). However, the influence of particular social media platforms on B2B firms' business outcomes remains under-researched (Salo, 2017). Indeed, understanding how to employ LinkedIn or similar media platforms effectively requires further investigation (Leek, Houghton, & Canning, 2019). Therefore, we aim to determine how B2B firms can manage LinkedIn to drive their sales and other intermediate outcomes.

In this study, we develop and test a framework based on social media marketing's influence (accounting for sales, technical, and social posts) on selling outcomes via an intervening mechanism (website visits) and a social exchange outcome (new followers; see Fig. 1). Social media have transformed the sales process and buyer–seller communication exchange in B2B settings (Enyinda et al., 2021, p. 992). In line with the idea of better connecting B2B marketing actions with financial outcomes (Mora Cortez & Johnston, 2017), our study focuses on the complete customer engagement process in LinkedIn that enhances sales revenue at the firm level. In addition to the focus on understanding social media from an organizational perspective, the use of longitudinal data distinguishes our study from related research that commonly explores social media influence at the salesperson level (e.g., Itani et al., 2017) and/or adopts a cross-sectional approach (e.g., Guesalaga, 2016). To the best of our knowledge, only two B2B marketing studies have empirically investigated social media outcomes at the firm level using longitudinal data (cf. Vieira et al., 2019; Mora Cortez & Ghosh Dastidar, 2022). However, these articles do not use a typology for post classification.

B2B social media communications are increasing in complexity, since text is "not limited to written language" but includes "images, video, kinetic movement and audio including spoken language and sound" (Mehmet & Clarke, 2016, p. 94). If posts are appealing to the

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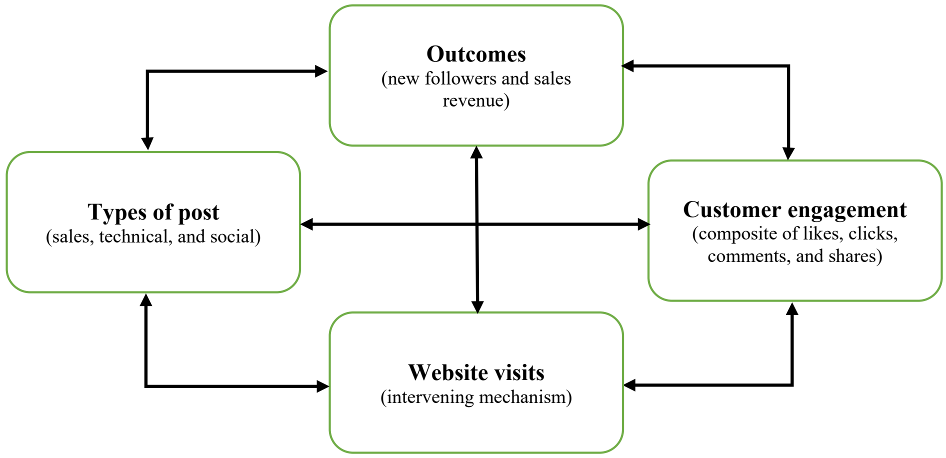

Fig. 1. Conceptual Framework.

target audience, managers (customers) can react in the form of likes, clicks, shares, and comments. Hence, the content of messages is an important element to drive engagement and reach a broader audience leading to new followers and an increase in the firm's sales potential (Prodromou, 2015). Furthermore, firms seldom exclusively rely on social media actions and often complement them with other online and offline actions (Tsimonis & Dimitriadis, 2014). For example, a B2B customer can be contacted by email or a phone call. Therefore, we ask the following research questions: (1) how does the content of posts on LinkedIn affect (a) engagement, (b) new followers, and (c) sales revenue? and (2) how do additional marketing actions create synergies (if any) with social media posting?

Extant B2B marketing research calls for further quantitative testing of social media influence, considering the uniqueness of the context (Kumar & Sharma, 2022). In this vein, Vieira et al. (2019, p. 1086) identify a theoretical gap in investigating digital marketing strategies in an emerging economy context, making B2B firms operating in Latin America an attractive setting for exploring our research questions. Moreover, start-ups possess high levels of discretion and are commonly born with a digital mindset, facilitating the integration of social media into the marketing strategy (Matties, 2012). Hence, using data[1] from a new B2B service firm (Est. 2017) in Latin America (operating primarily in Chile and Peru), we empirically test a vector autoregressive model with exogenous variables (VARX).[2]

The findings of the study contribute to the B2B marketing literature in several ways. First, we highlight the importance of acquiring new followers on LinkedIn for a B2B firm. The number of new followers is positively influenced by sales posts and website visits, which then positively influence both sales revenue and engagement. Specifically, a 1 % increase in new followers leads to 0.591 % and 0.512 % increases in sales revenue and engagement, respectively. These findings are important because B2B marketers can demonstrate to top managers that social media positively influence sales performance at the firm level. In addition, increasing new followers is a representation of relational trustworthiness as it positively influences engagement, an important constituent of long-term success of B2B firms (Vieira et al., 2019).

Second, we investigate the interrelations between social media and website visits. We acknowledge that websites are the digital face of every B2B firm (Miller, 2012). Our findings indicate that a 1 % increase in sales posts and new followers achieve 0.311 % and 0.274 % increases in website visits, respectively. Additionally, a 1 % increase in website visits leads to 0.356 % and 0.140 % increases in sales revenue and followers, respectively. These results highlight the role of B2B websites in accentuating the benefits of social media.

Third, we identify the effect of different post types on sales revenue. Interestingly, neither sales, technical, nor social posts drive sales directly; rather, website visits and followers mediate sales posts' effect on sales revenue. Further, we find that social posts positively influence the level of engagement and negatively influence the number of website visits, with a 1 % increase in social posts leading to a 0.294 % increase in engagement and a 0.056 decrease in website visits. These results suggest that firms need different approaches for achieving different marketing goals (e.g., engagement versus sales revenue). Thus, deploying social media marketing on LinkedIn is challenging and integrative, rather than simple and isolated.

2. Theoretical background

2.1. Social media adoption in B2B settings

Social media relate to internet-based platforms that allow the creation and exchange of user-generated content (e.g., Itani et al., 2017). Popular social media platforms include sites such as Facebook, Flickr, Instagram, LinkedIn, Reddit, Tik Tok, Twitter, and YouTube. Formally, social media are defined as "the technological component of the communication, transaction and relationship building functions of a business which leverages the network of customers and prospects to promote value co-creation" (Andzulis et al., 2012, p. 308). Social media have resulted in the transformation of communication practice, modifying how messages are developed, formulated, disseminated, and consumed (Mehmet & Clarke, 2016). Despite the expansion of social media usage in recent years, the adoption of social media by B2B firms has been slow compared with consumer (B2C) firms (Michaelidou, Siamagka, & Christodoulides, 2011; Iankova, Davies, Archer-Brown, Marder, & Yau, 2019). Consequently, scholarly research focusing on B2B social media is still in its infancy and offers narrow insight into the phenomenon (Trainor, Andzulis, Rapp, & Agnihotri, 2014; Vieira et al., 2019).

A key barrier to social media adoption in B2B settings is that many CEOs still believe that social media are not right for their organizations (Minsky & Quesenberry, 2015). This viewpoint results from their belief that the primary benefit of social media lies in lead generation, thereby creating the wrong impression that social media is appealing only to salespeople (Jackson, 2018). This finding is consistent with Itani et al. (2017, p. 65) who noted that "rather than at an organizational level, social media use in B2B sales is becoming popular at the salesperson

[1] The dataset spans 106 weeks from February 2019 to March 2021.

[2] The VARX model uses post type (sales, technical, and social), engagement behaviors (a composite of likes, clicks, shares, and comments), impressions, new followers, email campaigns, sales calls, website visits, and business outcome (sales revenue).

level as an individual initiative." At this level, B2B firms are mainly looking at how social media can be used to initiate sales (Bill et al., 2020). Hence, the challenge for researchers is to further explore how B2B marketers may take advantage of social media to drive customer engagement and company reputation, and to extend sales support to the buyer's purchase journey (Minsky & Quesenberry, 2015).

2.2. Social media deployment in B2B marketing settings

Social media marketing emerges from the idea of "utilizing the relationships, connections and insights available in social channels to facilitate a better experience in both buying and selling" (Berkman, 2014, p.1). Scholarly research argues that the three main selling facets of social media are (1) acquiring insights into prospects, existing customers, and influencers, (2) connecting to relevant actors through networking and consistent dialogue, and (3) engaging actors through valuable content (Ancillai et al., 2019, p. 297). These facets appeal not only to the customer-specific level (peer-to-peer communication) but also to the customer-centric level (network communication; Ogilvie et al., 2018). The network communication tenet is consistent with the view of selling as a service ecosystem (see Hartmann, Wieland, & Vargo, 2018), which emphasizes that selling and value co-creation are embedded in social systems (Ancillai et al., 2019). Hence, a successful social media approach builds over a dynamic, multi-actor flow of information. Through social media, B2B managers can participate in different networks creating new "spaces" for sharing information.

The idea of a new, broader perspective on B2B social media influence is becoming attractive to practitioners and researchers alike. For example, Vieira et al. (2019) show that social media activity (measured by likes, shares, and comments on Facebook and Instagram) positively influences the sales revenue of a Brazilian B2B firm. The overarching theoretical underpinning leading this shift in focus from lead generation is *branding* being perceived as a social phenomenon (Jackson, 2018). Social media can be organizationally representative of all the functions of a firm and serve customers by responding to questions and influencing both rational and emotional reactions to the brand (Minsky & Quesenberry, 2015). Thus, social media have the potential to enhance B2B brand equity (Rapp, Beitelspacher, Grewal, & Hughes, 2013). Indeed, Siamagka, Christodoulides, Michaelidou, and Valvi (2015) demonstrated that perceived image enhancement from using social media is the strongest predictor of perceived (social media) usefulness. Further, social media help create content that tells stories, appeals to emotions, and sparks conversations (Jackson, 2018). Overall, the dynamism of social media allows a B2B firm to foster customer and employee relationships by reinforcing the social element of selling industrial products/services (Swani et al., 2014; Bill et al., 2020).

2.3. Social media and the selling process

For effective deployment of B2B social media, a strategy needs to be in place to influence the different steps of the selling process (Andzulis et al., 2012). More specifically, Agnihotri et al. (2012) suggest that a social media strategy should entail (1) the outlining of core objectives and aspirations of salespeople, (2) the execution of a key approach to gain success and engage customers, (3) the monitoring of competitors' actions, and (4) the assessment of performance (p. 342). Social media can be integrated with the traditional sales process (understanding the customer, approach, needs identification, presentation, close, and follow-up) and can positively contribute to every step in the process. First, to increase the *firm's customer understanding*, social media allow firms to "listen" to customers by simply monitoring the complaints, inquiries, concerns, and experiences that are being discussed online. Second, to facilitate the *approach*, social media enable liking, sharing posts, responding to comments, or debating in thematic groups, which bring opportunities to interact. Third, to catalyze the *identification of the needs*, social media allow effective communication, reducing the number of steps required to understand the specific needs of a customer. Fourth, to ease the *presentation*, social media enable the possibility of educating customers by keeping them informed in a language that they can understand, often adopting terms from customers' messages to brands. Fifth, to drive the *close*, social media allow for handling objections effectively and providing testimonials. Sixth, to enhance the *follow-up*, social media enable informing customers about interesting events, conducting exploratory surveys on satisfaction, asking for referrals, and communicating the availability of new products/services (Lacoste, 2016; Ogilvie et al., 2018; Andzulis et al., 2012; Moore et al., 2015). Hence, social media deployment might influence sales revenue, search for information (e.g., website), and customer engagement at the organizational level.

2.4. LinkedIn as a professional networking site

LinkedIn is the top social media platform used by B2B firms, with 89 % penetration (Jackson, 2018). LinkedIn's popularity emerges from its capacity for assisting in identifying names of decision-makers and buyers, generating leads, building customer relationships, and having a strong reputation among B2B marketers (e.g., Itani, Agnihotri, & Dingus, 2017; Lack & Chong, 2016; Jackson, 2018; Diba, Vella, & Abratt, 2019). LinkedIn allows individuals to create firm-level accounts (focus of this study) to communicate via posts with the nearly 700 million active users on the platform (Bump, 2020). A firm's account is generally managed by account administrators who are responsible for the firm's posts and what customers and other market actors will "see" in the feed, allowing actors to follow network activities and stay informed by consuming recommended content (Bhatt & Saltman, 2017; LinkedIn, 2020a).

Interestingly, the B2B marketing literature is well versed in the contribution of posting content on LinkedIn from a reciprocal network development view. Reciprocity is central to strengthening business relationships and involves behaviors that can sustain mutual benefits over a period of time. Particularly, the shared content has potential value to the creator, disseminator, and recipient of the post. The creator of content sees their ideas made real and available to others, the disseminator of the content is afforded recognition for the finding and redistributing an item of perceived interest to others in the network, and the recipient benefits from the usefulness of the content and may add to the size of the creator's network of contacts (Quinton & Wilson, 2016, p. 16). However, the assumption is that the published content has an adequate degree of novelty and fulfills a clear communication goal. The latter has not been explored in extant B2B marketing research, representing a knowledge gap that this study aims to bridge. The next section describes our conceptual model (see Fig. 1).

3. Linkedin social media marketing model

3.1. Social media engagement on LinkedIn

LinkedIn functionalities and mechanisms enable social media marketing by allowing individuals and firms to engage through posts. Customer engagement is defined as a *psychological state resulting from specific interactive episodes that a customer experiences with a focal agent or object* (Leek et al., 2019, p. 115). Extant research indicates that LinkedIn content itself helps users to feel engaged and engagement can be studied by focusing on users' behaviors (e.g., Sundström, Alm, Larsson, & Dahlin, 2021; Mora Cortez & Ghosh Dastidar, 2022).

The most basic engagement is simply paying attention to a post. LinkedIn defines this reaction as "impressions." The impression is the total number of times at least 50 % of a post was visible for more than 300 ms (Sehl & Baird, 2020). Then, LinkedIn clusters six different types of engagement behaviors (like, celebrate, support, love, insightful, and curious) as "reactions." LinkedIn defines reactions as "a set of expressions that offers users a way to more easily participate in conversations and communicate with their network." This set of reactions was updated in April 2019 since previously only the *like* option was available (see LinkedIn official blog). Another way to react to a post is via the "share" option, which allows users to share posts on their LinkedIn feed. The main difference between a share and a reaction (e.g., like) is that the former provides the opportunity to include a comment and *hashtagging* (using the # and @ functionalities) entities (e.g., managers, firms) by which the firm wants to be seen. Next, "clicks" are a heuristic that indicates whether a post's call-to-action worked. Clicks refer to the total number of signed-in users that clicked on a post (Sehl & Baird, 2020). Finally, the most traditional component of engagement is commenting via a text response. Note that impressions are the baseline for all other forms of customer engagement.

3.2. LinkedIn followers

Growing the number of followers of a firm's LinkedIn page is deemed the most valuable marketing objective on the platform (Bump, 2020), especially for start-ups (Banerji & Reimer, 2019). Increasing the total number of followers can lead to greater organic reach and more robust audience insights (Lessard, 2019). Having a wide follower base is a crucial step for a firm to build a community on LinkedIn, thereby enhancing the likelihood of effectively disseminating a firm's communications. Following a LinkedIn page is a clear, direct behavior indicative of a customer's/manager's interest in learning about the firm's products and services, employees, and firm-related market activities. LinkedIn (2020b) indicates that followers are the lifeblood of a business, and it is not easy to get them, with the average LinkedIn user following just six companies. Hence, recommendations for B2B marketers on how to grow the number of followers are imperative for a more complete understanding of digital marketing strategy (Bump, 2020; Prodromou, 2015).

3.3. LinkedIn content classification

Prior research has noted that a post's content (relevant versus irrelevant) can influence the effectiveness of social media use (see Bill et al., 2020). Thus, analyzing posts' content is essential for a more thorough comprehension of social media in B2B settings. Previous studies have identified different theoretical approaches to social media content classification. Such approaches include message appeal (e.g., Swani, Milne, Brown, Assaf, & Donthu, 2017; Swani et al., 2014), hierarchy-of-effects (e.g., Juntunen, Ismagilova, & Oikarinen, 2020), or main communication purposes (information sharing, problem solving, and public relations; Leek et al., 2019), but none of them focus on LinkedIn. The two studies examining LinkedIn posting do not differentiate by content type. On one hand, Sundström et al. (2021) explore whether certain aspects (extended self, shared values, and authenticity) of the content can influence customer engagement. On the other hand, Mora Cortez and Ghosh Dastidar (2022) investigate the effect of perceived brand personality (sincerity, excitement, competence, sophistication, and ruggedness) of posting on customer engagement. Hence, a clear view on how to categorize B2B LinkedIn posting is missing.[3]

We adopted a grounded theory approach (e.g., Corbin & Strauss, 2014) to identify how firms classify LinkedIn content in B2B settings. We conducted pre-study qualitative interviews with 15 U.S. B2B practitioners involved in senior marketing roles to explore the different perspectives that a LinkedIn post can take to engage a target audience (Table 1). Following Corbin and Strauss (2014), we adopted a general open coding approach in the first phase to register the basic intentions behind LinkedIn posting. The specific technique used is *in vivo* coding (Charmaz, 2014), line by line. Next, in the second stage, we applied axial coding to enrich the open codes with B2B social media literature, analyzing the definitional properties of the themes and reassembling the data to ensure congruity to the nascent categorization (Charmaz, 2014). Finally, we conducted selective coding, defined as the refinement and unification of the theory (Corbin and Strauss, 2014). At this stage, we regrouped the previous axial categories into a more abstract, integrative framework (see Table 1).

The pre-study participants identified three different appeals for LinkedIn posts: (1) social, (2) technical, and (3) sales. Social posts are focused on the human nature of the business experience (i.e., people being the main element of a post) and "feel good" communication, including content on anecdotes from field visits, greetings on a special date (e.g., national day), managers' awards, and interaction among colleagues and/or customers (e.g., in a webinar). Social posts are expected to affect sales by generating emotional value for the customer via signaling a positive image of the firm and its offerings or the set of associations that a focal firm represents (Campbell, Papania, Parent, & Cyr, 2010). Further, social posts foster the reputation of a firm, which inhibits opportunism since word of opportunistic behavior would spread through the network of firms in which the focal firm is embedded, resulting in the loss of future contracts (Suh & Houston, 2010, p. 746). In addition, through social posts, potential customers can recognize shared values that are key to enhancing coordination and performance, since buyer and seller internalize common goals (Kashyap & Sivadas, 2012).

Technical posts are focused on the "hard" knowledge and competencies (e.g., law, engineering, chemistry) of the business experience, including content in the form of white papers, case study reports, industry news, and empirical data on market trends. Technical posts are expected to affect sales by generating trust for the customer by leveraging knowledge of emerging technologies, non-branded products/services, and the needs of the market. Trust in a potential business partner may dissipate doubts regarding future behavior and performance. Furthermore, technical posts can enhance the perception of the firm's competence by highlighting work experience and expertise with a job (e.g., understanding and catering to customer needs; Waseem,

Table 1
LinkedIn Content Coding Scheme.

Open coding	Axial coding	Selective coding
Focus on greeting an employee	*Social*	*LinkedIn B2B posting*
Focus on visiting decision-makers in a customer site		
Focus on receiving an award		
Focus on supporting a charity		
Focus on social dynamics among employees		
Focus on celebrating a traditional day-off, industry day or profession day		
Focus on specialized/scientific white papers	*Technical*	
Focus on laboratory/test reports		
Focus on industry trends discussion (e.g., sustainability)		
Focus on legislation affecting industry development		
Focus on new technologies linked to products/services		
Focus on analyzing reports linked to target industries		
Focus on own product/service features	*Sales*	
Focus on new business alliances		
Focus on new prices (e.g., discounts)		
Focus on launching a new offering		
Focus on a customer referral		
Focus on benefits derived from offerings		
Focus on closing a deal		
Focus on firm performance indices		

[3] We discussed the three content classification approaches identified in prior literature with 33 U.S. practitioners during a workshop. The participants concluded that none of the approaches relates to how they really classify posts.

Biggemann, & Garry, 2018). Hence, technical posts contribute to the belief that a focal firm may fulfill its promises by being consistent, reliable, and responsible (Suh & Houston, 2010, p. 746).

Sales posts are focused on the products/services being marketed, including content on new product/service features, new or updated marketing channels, new or updated pricing (e.g., discounts), value propositions, and customer assessments/referrals. Sales posts are expected to affect sales by generating awareness of the products/services of B2B firms because awareness is associated with market performance (Homburg, Klarmann, & Schmitt, 2010). In addition, sales posts contribute by providing accurate and timely information about a firm's offerings, which enables market penetration and entry into new markets (Enyinda et al., 2021). Sales posts may also portray economic benefits by explaining how customers would not be able to conduct certain tasks without the help of the firm (Candi & Kahn, 2016). Overall, sales posts highlight availability, business success, and desire to serve the market.

3.4. Website as a key platform for business development

Cultivating a satisfactory online B2B customer experience requires that the available platforms have a high level of credibility and consistency across them, enabling a hassle-free and reassuring experience (McLean, 2017). Recent studies identify that a central path in increasing digital marketing effectiveness is generating traffic from social media to the organization's own website (Karjaluoto, Mustonen, & Ulkuniemi, 2015). B2B websites are primarily used to share information and maintain knowledge (Krings, Palmer, & Inversini, 2021). Hence, websites' influence on advancing customers through the sales funnel involves adequate levels of information quality and trustworthiness (McLean, 2017). If the browsing experience is satisfactory, customers can respond more positively to brand positioning elements (Virtsonis & Harridge-March 2008), which increases the willingness to purchase.

A B2B firm's website is usually deployed to provide information to customers in an organized manner and facilitate sales (Chakraborty, Lala, & Warren, 2003). Moreover, a firm's website is frequently the first contact that stakeholders have with the organization, being an important instrument for nurturing a consistent image to stakeholders (Simões, Singh, & Perin, 2015, p. 60). Thus, a firm's website is a vehicle of corporate communication showing its commitments to various audiences (Esrock & Leichty, 2000). The potential usefulness of a website as an integral part of the online B2B customer journey depends on a coherent articulation of the website's communication elements (i.e., components of a website that are used to convey meaning, information, or messages; Virtsonis & Harridge-March 2008), where structural elements (i.e., sections/tabs) are the core. The two most common structural elements are (1) company profile/overview/financial and (2) solutions/services/products sections (Virtsonis & Harridge-March 2008, p. 708). Hence, customers have expeditious access to information on both the corporation and its offering. Based on the previous discussion, it is reasonable to infer that B2B customers can dynamically move back and forth through LinkedIn and a firm website, and, thus, the latter might also relate to customer engagement and sales revenue (see Fig. 1).

4. Method

4.1. Research setting

The empirical setting is a Latin American B2B consultancy company that operates across the region, but primarily in Chile and Peru. Established in October 2017, its marketing activities are concentrated on LinkedIn. The firm does not have any other social media account and does not utilize offline or other traditional advertising media but delivers information to the market via email and sales calls. The main services provided are training, seminars, applied research, and consultancy; with about 45 % of services (based on annual revenue) being classified as unplanned (i.e., demand is generated a couple of weeks before the activity via LinkedIn communication, emailing, and phone calls) and 55 % of services being classified as planned (i.e., negotiated through a long period of time, in many cases for 9–18 months). The broad nature of the services provides an ideal setting to analyze the association between LinkedIn posting and sales revenue.

Such knowledge-intensive consultancy firms are new in the region where several actors emerge and disappear after one or two years. However, the focal firm consolidated its presence during the 2019–2021 period and expectations for 2022 are positive despite the ongoing COVID-19 pandemic. In parallel, two competitors have also consolidated their position in the two main target countries, creating an increasing level of market competition. The longitudinal data span 106 weeks from week 8 in 2019 to week 9 in 2021. Given our focus on social media marketing, the consultancy firm provides an appropriate setting to answer our research questions.

4.2. Data

For our study, we consider *sales revenue*, *number of new followers*, *number of sales-related LinkedIn posts*, *number of technical-related LinkedIn posts*, *number of social-related LinkedIn posts*, *engagement,* and *website visits* (all measured at the weekly level) as endogenous variables.

Sales revenue. We aggregate and add the total sales (in USD) from the Chile and Peru markets at the weekly level. The date of the sale 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 confirmation was sent, or a direct payment was made.

New followers. We aggregate 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.

Type of post. The posts shared by the B2B firm on its LinkedIn page fell into three categories (*sales posts*, *technical posts*, and *social posts*) based on the content on the posts. Two independent coders (one senior marketing researcher and one partner in the focal firm) analyzed the content data of 146 posts (accounting for the whole research period). The agreement rate was 96.6 % with only five posts coded differently. Disagreements were resolved through discussions. For each type of post, we measure the total number of posts at the weekly level.

Engagement. For each week in the period of observation, we compute the total number of reactions[4] (e.g., like, love, celebrate), clicks, comments, and shares based on all posts on the focal firm's LinkedIn page. Following convention in prior literature, we combine the counts of all these metrics to form an *engagement* variable (e.g., Vieira et al., 2019). The *engagement* variable represents user behaviors (Tirunillai & Tellis, 2012; De Vries et al., 2017) over which the firm has little or often no control.

Website visits. More people visiting the focal firm's website could be a signal of interest in the firm's services and can positively affect the firm's sales revenue and follower count on LinkedIn. Similarly, type of posts and engagement on LinkedIn can drive traffic to the firm's website. We compute this variable as the total number of weekly visits to the focal firm's website.

Control variables. We control for other factors that could affect the focal firm's sales revenue, new followers, engagement, and type of post. Namely, we control for impressions, events, sales calls, emails, and general interest regarding the service category in which the focal firm operates. Additionally, we include an indicator to identify whether a given week belonged to the pre COVID-19 period or not, given that the pandemic may have affected buyer–seller relationships (Mora Cortez & Johnston, 2020). Impressions refer to the total number of exposures of a

[4] Likes constitute 89.75% of all reactions in our data.

Table 2
Results of Granger Causality Tests.

DV Granger-caused by…	Dependent Variables (DVs) Sales	New Followers	Sales Post	Technical Post	Social Post	Engagement	Website Visits
Sales	–	0.097	n.s.	n.s.	0.026	0.047	0.001
New Followers	n.s.	–	0.047	0	n.s.	0.069	n.s.
Sales Post	0.000	0.007	–	0.098	0.063	0.014	0.013
Technical Post	n.s.	n.s.	n.s.	–	n.s.	0.033	n.s.
Social Post	n.s.	0.021	0.015	n.s.	–	0.052	0.005
Engagement	0.081	0.052	0.047	n.s.	n.s.	–	n.s.
Website Visits	0.008	0.014	0.019	n.s.	n.s.	0.000	–

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

post to users on LinkedIn[5] and can possibly affect the firm's sales revenue, new follower count, and the performance of its posts. Like other variables in our model, impressions were also aggregated for all posts at the weekly level. 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 people from different firms and potential customers and could be a source of influence on a firm's sales and new follower count on LinkedIn. Sales calls are buyer–seller telephone interactions initiated by the seller to inform about its services. Emailing is communication via email initiated by the seller to inform about its services. Google search is the market-initiated query for the focal firm's main service category on Google[6] (provided by Google Trends). It captures organic market interest in competitors and substitutes.

4.3. Model specification

In this study, we are interested in the effects of type of post (sales, technical and social) and engagement on sales revenue and the number of new followers 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 effects (elasticities) over time by using impulse response functions. We begin by conducting the Granger causality test to determine whether sales, number of new followers, type of content, engagement, and website visits are endogenous. In the test, we use up to four lags and report the lowest p-values in Table 2 (e.g., De Vries et al., 2017). The results show that 22 out of the 49 effects are significant at 5 % level of significance, providing evidence of Granger causality among an adequate number of variables.

Next, we use the Phillips-Perron (PP) test to evaluate the stationarity of our time series (Pauwels, 2004). Since we include a constant term (α) and a deterministic time trend (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). 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 full dynamic system of the VARX model in Equation (1), where the vector of endogenous variables: sales revenue in USD (Sales), number of new followers (New_Fol), engagement (Engage), sales (Sales_Post), technical information (TI_Post), and social (Social_Post) posts on LinkedIn, and website visits (Web_Visits), 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). Additionally, we control for total weekly impressions (Impressions) on LinkedIn, average weekly Google search interest in the main service category (GTrends; 0–100) the focal firm operates in, 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 customers during the week, 0 otherwise), email communications (Email; 1 if emails were sent to potential customers during the week, 0 otherwise), 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 A and B.

Table 3
Unit Root Test Results (PP Test).

Variables	PP Test Statistic	Stationary?
Sales	−8.44*	Yes
New Followers	−6.16*	Yes
Sales Post	−7.50*	Yes
Technical Post	−10.99*	Yes
Social Post	−8.50*	Yes
Engagement	−8.61*	Yes
Website Visits	−4.19*	Yes
Search Interest	−9.47*	Yes
Impressions	−8.15*	Yes
Sales	−8.44*	Yes

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

$$\begin{bmatrix} ln(Sales_t) \\ ln(New\_Fol_t) \\ \ln(Engagement_t) \\ \ln(Sales\_Post_t) \\ \ln(TI\_Post_t) \\ \ln(Social\_Post_t) \\ ln(Web\_Visits_t) \end{bmatrix} = \begin{bmatrix} \alpha_{Sales} \\ \alpha_{New\_Fol} \\ \alpha_{Engagement} \\ \alpha_{Sales\_Post} \\ \alpha_{TI\_Post} \\ \alpha_{Social\_Post} \\ \alpha_{Web\_Visits} \end{bmatrix} + \begin{bmatrix} \delta_{t,Sales} \\ \delta_{t,New\_Fol} \\ \delta_{t,Engagement} \\ \delta_{t,Sales\_Post} \\ \delta_{t,TI\_Post} \\ \delta_{t,Social\_Post} \\ \delta_{t,Web\_Visits} \end{bmatrix}$$

$$+ \begin{bmatrix} \theta_{1,1} & \cdots & \theta_{1,4} \\ \vdots & \ddots & \vdots \\ \theta_{7,1} & \cdots & \theta_{7,4} \end{bmatrix} \times \begin{bmatrix} X_{1,t} \\ X_{2,t} \\ X_{3,t} \\ X_{4,t} \end{bmatrix} + \begin{bmatrix} \beta_{1,1} & \beta_{1,2} \\ \vdots & \vdots \\ \beta_{7,1} & \beta_{7,2} \end{bmatrix} \times \begin{bmatrix} ln(Impressions_t) \\ ln(GTrends_t) \end{bmatrix}$$

[5] https://www.linkedin.com/pulse/do-you-know-what-impressions-how-measured-viewability-gostory-media/.
[6] We looked at the searches for the main two competitors, but no data were available (due to insufficient datapoints).

Table 4
Parameter Estimates of the VARX Model.

	Ln (Sales)	Ln(New Followers)	Ln (Sales Post)	Ln(TI Post)	Ln (Social Post)	Ln (Engagement)	Ln (Website Visits)
$Ln(Sales)_{(t-1)}$	0.019	-0.010	-0.010	0.004	0.012	0.045*	0.005
$Ln(New\ Followers)_{(t-1)}$	0.401	0.230*	0.056	0.051	-0.027	0.294**	0.095
$Ln(Sales\ Post)_{(t-1)}$	0.691	0.290	-0.011	0.038	-0.028	-0.147	0.329**
$Ln(TI\ Post)_{(t-1)}$	-0.444*	-0.311	-0.130	-0.144	-0.042	-0.244	0.117
$Ln(Social\ Post)_{(t-1)}$	-0.731	0.114	-0.297**	-0.038	0.008	-0.024	-0.130
$Ln(Engagement)_{(t-1)}$	0.255	-0.046	0.029	0.027	0.052	-0.039	-0.071
$Ln(Web\ Visits)_{(t-1)}$	0.289	0.161	0.033	-0.084	0.005	0.065	0.364**
Constant	-0.091	0.143	-0.238	0.046	-0.113	1.367**	2.141**
Trend	-0.018	0.007	-0.001	0.002	0.000	-0.001	-0.003
Impressions	-0.027	0.048*	0.055**	0.039**	0.053**	0.436**	0.058**
Events (dummy)	1.742*	0.387**	-0.160*	0.023	0.199**	0.374*	0.010
Email (dummy)	0.594	0.101	0.298**	-0.075	-0.215*	-0.187	0.040
Sales_Call (dummy)	0.794	-0.020	0.105*	-0.039	-0.013	-0.210	0.176
Covid (dummy)	0.094	0.800**	-0.094	0.032	-0.235	-0.750**	-0.312
GTrends	-0.234	-0.003	0.020	-0.026	0.001	-0.101*	−0.016
R-square	0.217	0.679	0.501	0.305	0.320	0.800	0.660

Notes: The autoregressive terms are all smaller than one in absolute value.
* $p < .10$;
** $p < .05$.

Table 5
Portmanteau Test for Autocorrelation.

Lags	Test Statistic	Degrees of Freedom
1	14.08	NA
2	55.88	49
3	126.14	98
4	175.25	147
5	209.82	196
6	262.93	245
7	307.91	294
8	362.44	343
9	407.68	392
10	453.32	441

Notes: The null hypothesis of the test is no serial correlation at lag order h (=10). The Portmanteau test is valid only for lags larger than the VAR lag order; N = 96. All *t*-statistics are non-significant at α = 0.01.

$$+\sum_{j=1}^{J}\begin{bmatrix}\Phi_{1,1}^{j} & \cdots & \Phi_{1,7}^{j}\\ \vdots & \ddots & \vdots\\ \Phi_{7,1}^{j} & \cdots & \Phi_{7,7}^{j}\end{bmatrix}\times\begin{bmatrix}ln(Sales_{t-j})\\ ln(New\_Fol_{t-j})\\ \ln(Engagement_{t-j})\\ \ln(Sales\_Post_{t-j})\\ \ln(TI\_Post_{t-j})\\ \ln(Social\_Post_{t-j})\\ ln(Web\_Visits_{t-j})\end{bmatrix}+\begin{bmatrix}\varepsilon_{t,Sales}\\ \varepsilon_{t,New\_Fol}\\ \varepsilon_{t,Engagement}\\ \varepsilon_{t,Sales\_Post}\\ \varepsilon_{t,TI\_Post}\\ \varepsilon_{t,Social\_Post}\\ \varepsilon_{t,Web\_Visits}\end{bmatrix} \quad (1)$$

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 Impressions and GTrends and $\Phi_{i,i}^{j}$ are parameters of the lagged endogenous variables representing direct and indirect effects among the endogenous variables. Finally, the error terms of each endogenous variable are represented by ε_t.

We use the Akaike information criterion (AIC), Schwarz information criterion (SC), and Hannan-Quinn information criterion to conclude that the number of lags for the endogenous variables in the VARX model is one. On estimating the model, we find that the absolute values of the autoregressive parameters (Φs) are all less than 1 (see Table 4), which indicates that the VARX model is stationary. We test the assumption that there is no autocorrelation between the residuals of the VARX model using the Portmanteau autocorrelation test. We conduct the test up to the 10th lag and for each lag, the test indicates no autocorrelation among the residuals (see Table 5).

To accurately interpret the parameters of the endogenous variables in the VARX model, we use cumulative orthogonalized impulse response functions. To do this, we use a Cholesky decomposition of the error terms after estimating the VARX model, which transforms the error vector into having elements that are uncorrelated. Using Cholesky decomposition helps account for the problem of contemporaneous correlation between elements of the error vector (Evans & Wells, 1983). We use all possible orderings (5,040) among the endogenous variables to compare the average relative effects among the endogenous variables (e.g., De Vries et al., 2017).

5. Findings

5.1. Impulse response functions (IRFs)

In line with previous VARX applications in marketing (e.g., De Vries et al., 2017; Vieira et al., 2019), we discuss the cumulative elasticities from the IRFs, considering the response of performance eight weeks ahead (see Table 6). We identify the significant cumulative effects (at α = 0.10 level) based on confidence intervals computed using bootstrapping with 5,000 runs. We find that new followers are a key element in deploying social media marketing because they help generate sales and engagement with a 1 % increase in new followers leading to a 0.591 % increase in the amount of sales revenue and a 0.512 % increase in the level of engagement, respectively. The former effect could be due to the fact that followers are potential customers who may be convinced by the firm's value proposition. An explanation for the latter effect might be that more followers increase the reach of the firm's LinkedIn messages (i.e., higher post visibility), which, in turn, increases the total level of engagement on the posts. We also observe that the effect of new followers lasts longer for engagement than for sales revenue (weeks 0–2 versus weeks 0–1, respectively). Interestingly, an impulse on engagement does not influence sales, which is different from the response (0.06) found by Vieira et al. (2019) who accounted for sales as the sum of payments while we use the sum of the purchase orders in USD (i.e., Vieira et al. considered a date in time later than when the selling actually happened). Differences in platform specific mechanisms (i.e., LinkedIn versus Facebook) may also help explain the differences in outcomes between this study and Vieira et al. (2019).

Further, we find that website visits affect the number of new followers significantly, but there is also a feedback effect (i.e., new followers affect website visits). A 1 % increase in website visits leads to a 0.140 % increase in the number of new followers from week 0 to week 1,

Table 6
Cumulative Elasticities of the Endogenous Variables.

Impulses in …															
Responses of …	Followers			Website Visits			Sales Posts			Technical Posts			Social Posts		
	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
Sales*	0.591	0	1	0.356	0	1	–	–	–	–	–	–	–	–	–
Followers	0.878	0	1	0.140	0	1	0.212	0	2	–	–	–	–	–	–
Sales Posts	–	–	–	–	–	–				–	–	–	–	–	–
Technical Posts	–	–	–	–	–	–	–	–	–				–	–	–
Social Posts	–	–	–	–	–	–	-0.070	0	1	–	–	–			
Engagement	0.512	0	2	–	–	–	–	–	–	–	–	–	0.294	0	1
Website Visits	0.274	0	1				0.311	1	3	–	–	–	-0.056	2	3

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.

* Sales own effect is 3.405 (wear-in: week 0; wear-out: week 1); sales effect on engagement is 0.170 (wear-in: week 1; wear-out: week 2).

and a 1 % increase in followers leads to a 0.274 % increase in the number of website visits from week 0 to week 1. Our results are supported by the observation that the credibility of a B2B firm's website[7] and the quality of the information on the website have a significant effect on the online customer experience (Chakraborty, Lala, & Warren, 2003; McLean, 2017), which, in turn, leads to more followers (Prodromou, 2015). This is because practitioners that encounter LinkedIn information from the focal firm have not necessarily met the firm before, driving practitioners to visit the firm website (to develop a more complete understanding of the firm). A potential reason for the feedback effect may be that once a stakeholder becomes a follower, they might be interested in surfing the focal firm's website to obtain more detailed information about its activities (e.g., to download services brochures, to explore upcoming activities). Furthermore, website visits positively influence the amount of sales revenue; a 1 % increase in website visits creates a 0.356 % increase in sales revenue (from week 0 to week 1). While potential customers are reflecting on purchasing a firm's service, they may look for more cues of quality on the firm's website. Based on the positive elasticity, the website seems compelling in providing such cues. This result is consistent with Vieira et al. (2019) who found a 0.47 cumulative elasticity for own media.

When comparing sales posts, technical posts, and social posts, we find that none of them have an influence on sales revenue. A potential explanation for the lack of effectiveness of type of posts with respect to sales revenue might be the nature of B2B buyers involving several practitioners, quantitative evaluation of value propositions, and a complex decision-making process (Lilien, 2016). Sales posts do not have the power to increase B2B purchase intention directly, but they may serve to activate the buying decision (Zinkevich & Ghekiere, 2019). We find that sales related posts directly influence the number of new followers and website visits with a 1 % increase in sales posts leading to a 0.212 % (from week 0 to week 2) and a 0.311 % (from week 1 to week 3) increase in new followers and website visits, respectively. A possible explanation could be that sales posts may not be able to adequately satisfy the information needs of potential customers who may prefer to obtain more information from the firm's website (McLean, 2017). Additionally, potential customers may recognize the usefulness of the services offered and aim to learn about the firm in a stepwise procedure by becoming a follower (Lessard, 2019). We also find that the number of sales posts has a negative influence on the number of social posts. A 1 % increase in sales posts leads to a 0.070 % decrease in social posts (from week 0 to week 1). There might be several explanations for this effect. For example, the focal firm may not want to saturate the market with too many posts and thus choose one type of post over the other. In a post hoc conversation with one of the focal firm's owners, it was indicated that the firm does not tend to publish social posts since their content is commonly based on the services already sold.

While technical posts are not associated with any other endogenous variable in the model, social posts negatively influence website visits. A 1 % increase in the number of social posts leads to a 0.056 % decrease in the number of website visits (from week 2 to week 3). A possible explanation is that the focus on individuals and positive feeling linked to social posts deviate the attention from the core business of the firm, limiting the interest in additional information regarding the organization and/or its services.

Furthermore, we find that both social posts and sales revenue positively influence the level of engagement. A 1 % increase in the number of social posts leads to a 0.294 % increase in engagement (from week 0 to week 2). A potential reason might be that social posts generally possess relatively more emotional appeal, which has been shown to be engaging in B2B digital communication (e.g., Swani et al., 2014). A 1 % increase in sales revenue leads to a 0.170 % increase in the level of engagement (from week 1 to week 2). This may be due to the fact that purchase of a service implies higher trust among customers towards the focal firm, and consequently, such customers are keen to manifest their support in an online environment. We depict the integrative causal network for social media marketing in Fig. 2.

5.2. Own effects and control variables

We find evidence for two noteworthy own effects. Sales positive own effect indicates that a 1 % increase in sales revenue leads to a 3.405 % increase in sales revenue from week 0 to week 1. Hence, at least temporarily, firms/practitioners participating in the focal firm's activities (services) may be informing others (through different channels) that they purchased a service, which, in turn, can influence other firms/practitioners to purchase from the focal firm. In addition, the focal firm may be using extant sales as a cue for solvency (success) and convince other managers (firms) to purchase services. Prior marketing literature is conclusive on the positive effect of referrals in B2B settings (e.g., Hada, Grewal, & Lilien, 2014), because industrial firms prefer to work with well-established suppliers. Moreover, followers' positive own effect informs that a 1 % increase in followers leads to a 0.878 % increase in followers from week 0 to week 1. A potential reason for the significant own effect might be that non-followers are informed about the connection's (user's) new status by LinkedIn algorithm since practitioners can see what firms their connections are following, fostering non-

[7] During the window of observation, a majority of the content of the focal firm's website remained unchanged. Minor changes included replacing information about past events with upcoming ones.

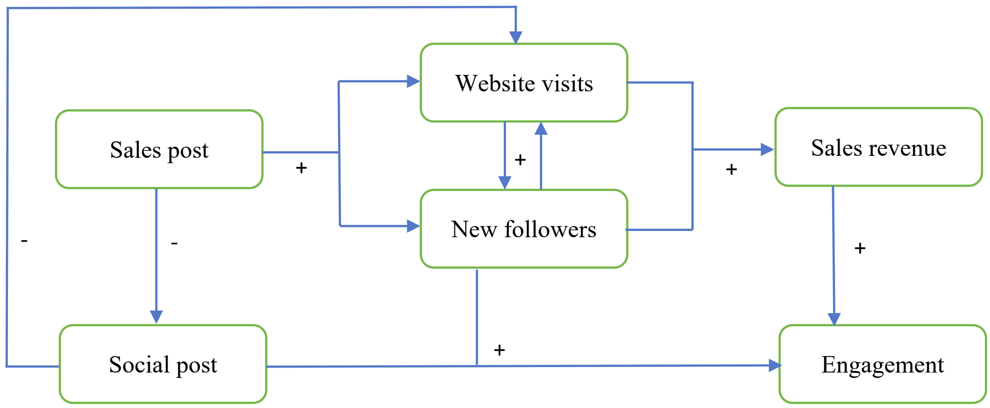

Fig. 2. Causal Network for the Endogenous Variables.

followers' willingness to follow the focal firm. This is consistent with emerging findings on B2B online brand communities (e.g., Bruhn, Schnebelen, & Schäfer, 2014).

Furthermore, we discuss some of the notable findings from the control variables parameters (see VARX results in Table 4). The number of post impressions affects followers, engagement, and website visits positively and significantly (φ = 0.048, φ = 0.436, and φ = 0.058, respectively). This result (combined with the previous analysis) indicates that impressions lead to followers directly and indirectly through engagement. Also, impressions capture the interest of competitors and other non-followers (e.g., customers of the competitors, business school scholars), who can review the website of the focal firm to be better informed about its activities or develop new ideas. The events dummy stimulates followers (φ = 0.387). This effect can be caused by the fact that events capture social encounters where the focal firm owners and managers meet new potential customers, and they become interested in the firm activities. Emailing and sales calls are related to sales post (φ = 0.298 and φ = 0.105, respectively). These results indicate that the focal firm manages its sales process by complementing social media, emailing, and sales calls to maximize their chances to close deals.

5.3. Robustness checks

To test the robustness of our findings, we selected a different modeling approach and re-specified the original VARX model. Following De Vries et al. (2017), the former assessment is based on estimating a linear model. We estimated this model by using a weighted least squares (WLS) estimator because this approach allows for different variances of the error terms in the different equations. Many of the results in the WLS model are equivalent to the VARX model (see Web Appendix C). However, the unrestricted VARX model is generalizable and enables capturing the complex interrelations among the type of post, web visits, engagement, followers, and sales revenue over time (De Vries et al., 2017). The latter assessment involved estimating a VARX model without the type of post variables (sales, technical, and social), which are prone to potential measurement error due to the manual coding (when classifying the posts). Measurement error could lead to biases in the parameter estimates (Wooldridge, 2010). The results are fairly consistent, and the simplified model fit is barely lower than the full model. The cumulative elasticities for the effects of website visits and engagement on followers and sales are consistent with the full model (see Web Appendix D), supporting the original results.

In addition, we hired a corporate communication consultant and a graphic designer to code the content assertiveness (CONTENT) and the image/video layout quality (DESIGN) of posts, respectively. To control for their potential effects, we included both variables as exogenous variables in the VARX model. The cumulative elasticities for the impulses in sales revenue, followers, website visits, sales posts, technical posts, and social posts are consistent with the proposed model (see Web Appendix E), except for the significant effect of sales posts on engagement (0.062; from week 2 to week 3). The latter can be explained due to many social posts being about individuals participating in the sold activities (and sales posts indirectly affect the number of participants in an activity), which are related to a higher level of engagement. In addition, the only significant effect of both variables is DESIGN on Engagement (φ = 2.73; $p = 0.03$). The consistency between the proposed model and the extended model might emerge from the minor standard deviations of both CONTENT (s.d. = 0.23) and DESIGN (s.d. = 0.41). Overall, the substantive findings are robust to the choice of different models and are not influenced by different VARX specifications.

6. General discussion

6.1. Theoretical implications

Prior conceptual literature has called social media use a "game-changer" (Kumar, 2015) and a "revolution in sales" (Marshall, Moncrief, Rudd, & Lee, 2012). However, scant empirical evidence has supported such claims (cf. Rodriguez, Peterson, & Krishnan, 2012). On one hand, one stream of the literature that is cautious about the benefits of social media marketing calls for "a more realistic discussion of social media's importance for sales" (Bill et al., 2020, p. 747). For example, Guesalaga (2016) indicates that salespeople rate social media usefulness for their jobs at the low-end, and social media sales impact depends on customers' interest in social media. On the other hand, another stream of the literature is emphatic about highlighting the opportunities that social media provide in engaging B2B customers. For example, Vieira et al. (2019) find that social media affect a B2B hub's capacity of generating new sales, noting that the firm actively uses social media in a digital echoverse system (p. 1086). Hence, when firms prioritize other selling channels, it may (negatively) influence the willingness of managers to correctly manage digital tools, limiting the potential of social media. It is important to highlight that the focal firm in this study purposively uses social media as a key factor for its sales process, thus positioning the selected research setting in the latter stream of the literature.

Our findings have several implications for B2B social media marketing literature. First, the LinkedIn action plan for small businesses (see LinkedIn, 2020a) is focused on the 3–2-1 strategy, which seems to be oriented to increase the level of engagement (likes, shares, clicks, and comments). However, such engagement is not related to either social exchange metrics (new followers) or firm performance (sale revenue). Our study addresses this gap and makes an important contribution in developing a grounded social media marketing theory. Additionally, we identify that growing the number of followers is the engine of successful B2B social media deployment. Our findings suggest that a 1 % increase in the number of followers leads to both more sales revenue (0.591 %)

and engagement (0.512 %). While increasing engagement may still be valid to defend the importance of using LinkedIn for the marketing department, increasing sales revenue can convince top management of the importance of LinkedIn at the firm level. Followers are the lifeblood for developing an online community, which positively drives a firm's brand equity (e.g., Zhu, Zhu, & Hua, 2019). Moreover, followers can be seen as actors that at least consider the followed firm as a valid market option but simultaneously demonstrate high levels of preference for and conviction in the firm under consideration. Hence, our finding about followers' pivotal social media role adds to the literature on integrated marketing communications, which posits social media influence as being in between commitment and consumption (see Batra & Keller, 2016).

Second, our results suggest B2B websites are relevant in deploying social media marketing successfully but less so than the number of followers. On one hand, website visits have a bidirectional association with the number of followers. In other words, more website visits lead to more followers, which further generates more website visits. Interestingly, the effect size associated with a 1 % impulse in new followers in comparison with a 1 % impulse in website visits is almost double (0.274 % versus 0.140 %). On the other hand, both website visits and followers lead to an increase in the amount of sales revenue. The former effect size (cumulative elasticity = 0.356) is substantially lower than the latter effect size (cumulative elasticity = 0.591). In addition, a 1 % increase in the number of sales posts influences both the number of website visits (0.311 %) and the number of new followers (0.212 %). Overall, integrating these findings expands social media marketing theory by showing that the main mechanism behind sales posts influencing sales revenue is a two-block indirect path (0.125 %, based on a simultaneous 1 % impulse on the base variables): (1) from sales post to new followers, and (2) from new followers to more sales revenue. The closest alternative path (0.110 %, based on a simultaneous 1 % impulse on the base variables) is: (1) from sales post to website visits, and (2) from website visits to more sales revenue. In that sense, we expand the results of previous research on B2B digital echoverse systems (e.g., Vieira et al., 2019), suggesting interesting associations among sales posts, new followers, website visits, and sales revenue.

Third, we provide details about the role of content classification in B2B social media. There is a dearth of empirical research on the effectiveness of different types of content in digital settings. Juntunen et al. (2020), Leek et al. (2019), and Swani et al. (2014) are notable exceptions, but they consider a different approach to content analysis in a distinct social medium (Twitter). Our findings contribute to uncovering the types of posts that are most decisive to foster sales growth and engagement. Surprisingly, neither sales, technical posts, nor social posts lead to sales revenue growth directly. Beyond the influences previously discussed, there are two significant (positive) effects emerging from post content. On one hand, a 1 % impulse on social posts achieves a 0.294 % response on the level of engagement. This indicates that focusing posts on individuals and their experiences derives in engagement from B2B firms/managers. This effect is superior to the influence of sales revenue on engagement, as a 1 % increase in sales revenue leads to a 0.170 % increase in engagement. However, social posts are not the main driver of engagement, since a 1 % impulse on followers achieves a 0.512 % response on the level of engagement. On the other hand, the number of sales posts negatively affect the number of social posts. A 1 % increase in sales posts leads to a 0.070 % decrease in social posts. Because our study investigates in depth a single firm, the identified negative association may represent a particular posting strategy. Future research may want to look at this issue in a more nuanced manner. Overall, one type of post (sales) influences sales revenue growth indirectly, while another type of post (social) affects engagement directly. Hence, our study is a response to calls for empirical research on the effectiveness of various content strategies (see Bill et al., 2020, p. 747).

6.2. Managerial implications

This study offers three key managerial implications, building over the fact the conceptual model can be adopted as a marketing tool and contributes to bridging the theory–practice marketing gap by assessing social media influence in an emerging economy setting. First, the results of the study suggest that sales posts and website visits are associated with the number of new followers and social posts. A follower can be understood as a pre-qualified prospect showing affinity to the firm. Hence, starting a conversation with followers will be easier than doing the same with a non-follower. Accounting for the number of followers is of utmost practical relevance as firms tend to compare themselves with competitors using this variable (Katona & Sarvary, 2014). By introducing a new service or communicating the value proposition of a long-lasting service on LinkedIn, firms can gain new followers because sales posts inform the market about what type of offerings a supplier can provide, diminishing the search costs for the buyer. In addition, a website can work similarly. A firm's website should show how valuable the company can be, and what the service/product portfolio includes (Vieira et al., 2019). This arouses the interest of potential customers deciding to become a follower, as they now aim to be informed about future services (or activities) of the firm in a more continuous manner.

Second, our findings suggest that LinkedIn followers, website visits, and types of posts can positively influence sales revenue. Indirectly, sales posts through website visits and new followers can affect sales outcomes. This discovery should nudge managers to not be afraid to publish sales-oriented posts (against the common market assumption of just posting more social/emotional content, e.g., Jackson, 2018). However, B2B firms should be cautious about overwhelming customers with sales posts since there might be a maximum level of tolerance (Prodromou, 2015). Also, it may be that the recency of the investigated firm drives a surprise element, motivating the market to be open to learn about the firm from "hard selling" efforts. This may not be the case for old, well-established firms in the market. Future research could explore the mechanisms identified in this study in more mature settings. Based on the comparative effect sizes of followers (0.591) and website visits (0.356) have on sales revenue, B2B managers should prioritize the creation of new followers when deciding what tactics to pursue in a social media environment. Hence, firms should explore the profile and characteristics of current followers to identify more "prone-to-be followers" among non-followers.

Third, our results suggest that the average effect of new followers and social posts on the level of engagement is positive. Since the effect of new followers (as an interested party in firm activities; 0.512) is more impactful on creating engagement than social posts (0.294), and in parallel, the effect lasts longer for new followers (three weeks versus two weeks), B2B managers should focus on driving new followers when aiming to foster engagement through posts. The LinkedIn algorithm rewards high reaction posts by letting them circulate more on the platform feed, allowing a post to become "viral" (see Bhatt & Saltman, 2017), potentially increasing the post's reach toward new prospects. While comparing engagement across competitors seems to be a recurrent practice (e.g., see Katona & Sarvary, 2014), this study does not find an association between the level of engagement and performance metrics. Therefore, we are cautious about recommending proactively managing engagement generation since it is not influencing any of the variables involved in the present social media marketing model. The social relevance of posting via LinkedIn may have positive effects on brand-building (De Vries et al., 2017), which is not directly accounted for in this study. Future research could analyze brand-building aspects during B2B social media deployment. Overall, this study enables managers to better understand the interrelations of social media marketing mechanisms in a B2B setting and provides initial evidence on how digital tools are intertwined with non-digital activities (e.g., sales calls). Hence, B2B marketers need to grasp the purchase decision as a complicated circular process (Vieira et al., 2019), partially influenced by social media actions.

6.3. Limitations and further research

Our study portrays B2B social media marketing mechanisms in LinkedIn that had not yet been examined together, addressing some important shortcomings of prior investigations. However, it has some limitations that provide fruitful avenues for future research. First, our results are based on data containing information on a single firm that commercializes services (and some of the services are launched in a contingent manner based on requests or emerging phenomena) mostly new to the market. This relatively spontaneous market approach may not be representative of more traditional B2B firms. Thus, we encourage researchers to replicate our study using data on capital goods or services acquired in a contractual setting. Second, cultural differences in the adoption of social media may be relevant (e.g., Feng, Zhang, & Lin, 2019). Future research could investigate social media marketing theoretical underpinnings in emerging economies in Africa, Asia, or Eastern Europe. Third, although we examine several engagement mechanisms, we do not consider other potentially relevant endogenous variables. For example, future studies might include a firm's profile visits in the analysis. Fourth, our results do not offer implications for managing engagement, which might have an influence on brand-building. For instance, future researchers could explore how posts contribute to brand experience dimensions (e.g., Brakus, Schmitt, & Zarantonello, 2009) and analyze how these dimensions relate to engagement. Fifth, while we identified that followers are essential to LinkedIn social media marketing, they may be acquired organically or via paid strategies (e.g., advertisements on LinkedIn). The focal firm only develops followers organically (i.e., using the credits to invite administrators' contacts) or naturally by users' proactive actions. Nevertheless, future studies may investigate a setting with both types of follower development strategies.

Sixth, our findings do not offer implications for technical posts. Such content might relate to boosting competence perceptions in the market but also might have negative consequences, nullifying its positive effects. For example, publishing technical posts can subsidize practitioners, fostering inactive participants or free riders. Prior social media literature elaborates on the threats of free riders because they essentially do not contribute to the success of an online community (e.g., Kamboj & Rahman, 2016). Further research could investigate the implications of publishing technical posts in a more detailed approach. Seventh, the data set did not comprise information about other potentially relevant sales process measures, such as the number of leads and cross-selling, because these variables are not yet registered by the focal firm at a weekly level. However, future studies might extend the set of dependent variables to produce a more complete view of social media marketing. Eighth, to facilitate the identification of who is viewing the posts and further scrutinize the actor role in the firm value chain (e.g., customer, employee, supplier), future studies may consider a research setting with firms using LinkedIn Navigator. Due to the cost and managerial effort associated with this service, medium- and large-sized firms are more likely to invest in LinkedIn Navigator. Similarly, further research could account for the different roles of new followers in the buying center or differentiate them by their relevance to the business.

Ninth, even though the focal firm has a quasi-invariant website, further studies could explore the effect of different content types (available on firms' websites) on sales revenue and engagement. Tenth, enhanced causal inferences can be made whether future research partners up with organizations to conduct experiments investigating the main links found in this study. The focal firm was not interested in pursuing an experimental design due to the high risk involved in any intervention. Eleventh, further research could connect social media engagement to segmentation in B2B settings (Mora Cortez, Clarke, & Freytag, 2021) or adopt alternative theoretical lenses (e.g., social exchange theory). Finally, this study focuses on LinkedIn as requested in previous research (e.g., Vieira et al., 2019). Investigating different social media is key for constructing a more robust social media marketing theory, because specific platform mechanisms may be divergent. In this vein, future research could adopt a more integrative approach and analyze the posts coming from multiple social media, moving toward a panel data environment. We hope these research opportunities, combined with our key findings, provide an impetus for continued social media research in the B2B marketing domain.

CRediT authorship contribution statement

Roberto Mora Cortez: Conceptualization, Formal analysis, Investigation, Methodology, Software, Writing – original draft, Writing – review & editing. **Wesley J. Johnston:** Writing – review & editing, Visualization, Validation, Supervision. **Ayan Ghosh Dastidar:** Writing – original draft, Visualization, Validation, Software, Methodology, Conceptualization.

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.

Web Appendix. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jbusres.2022.113388.

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