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# How B2B social media content strategies generate engagement across different social media platforms

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ABSTRACT

Social media (SM) has become an essential means of engaging key stakeholders for business-to-business (B2B) firms. As a result, academic research has paid increasing attention to the factors that drive SM engagement in business markets. Although studies have examined the types of SM content that generate higher engagement in B2B contexts, current research lacks deeper insight into message strategies across different social media platforms (SMPs). We address this knowledge gap by examining whether the use of SM content strategies by B2B firms varies across platforms and whether their effectiveness in generating engagement varies across SMPs. In doing so, we build a new SM content strategy framework focused on messaging functions that capture a broad set of message stakeholders. Using advanced Random Forest modeling, we analyze 1700 SM messages and related engagement data from 18 of the largest Canadian B2B companies based on their revenues. We advance current research knowledge by demonstrating how different message strategies across SMPs achieve higher engagement levels. The findings offer concrete insights for practitioners to effectively engage diverse stakeholders across different SMPs.

## 1. Introduction

By 2022, the number of business-to-business (B2B) buyers using social media (SM) to research and evaluate suppliers had increased fivefold relative to 2019, prompting B2B marketers to invest more heavily in SM (McClatchy et al., 2023). This shift is also reflected in academic interest, with 79 articles on B2B SM published between 2016 and 2020, compared to only 36 from 2009 to 2015 (Kumar & Sharma, 2022). Despite this increase in research, Liadeli et al. (2023) noted that this domain remains emergent. Cortez et al. (2023, p. 10) claimed that “There is a dearth of empirical research on the effectiveness of different types of content in digital settings”. Pardo et al. (2022) similarly observed that the research focused too heavily on tactics and not enough on strategies.

Interestingly, although several studies have already provided insights into which types of message strategies increase engagement in B2B, most extant research focuses on offering general explanations, concentrating on one social media platform (SMP) at a time (Pelletier et al., 2020). Little is known about how firms use platforms such as LinkedIn, Twitter (now known as X), and Facebook for various purposes or whether distinct message strategies effectively generate engagement across diverse contexts. Although SMPs have distinct characteristics and strengths for messaging and are likely to attract varied stakeholder audiences, extant research remains surprisingly silent on whether firms should tailor their content strategies to each platform and which message strategies foster higher engagement in varied contexts. For practitioners, understanding which content strategy works best on each platform is highly valuable.

An examination of social media engagement research reveals two challenges in existing studies that hinder the development of context-specific explanations. First, SM message content strategies (SMMCS), defined as firms' efforts to incorporate “useful, relevant, compelling, and timely” (Holliman & Rowley, 2014, p. 269) content in their SM messages to generate engagement (Li et al., 2021), have primarily been studied through conceptualizations that are narrow in their scope in terms of message functions, addressed stakeholders, and industry scope, thus being suboptimal for contextual explanations. Second, a surprisingly large number of studies have employed descriptive methods and inferential statistics (Juntunen et al., 2020; Leek et al., 2019; Zhang & Du, 2020). Additionally, many studies have relied on various regression-

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based approaches to predict the impact of SMMCS on engagement (Cheng et al., 2021; Deng et al., 2021; McShane et al., 2019; Shahbaznezhad et al., 2021; Yuen et al., 2023). Traditional regression-based methods are not well-suited for applications involving nonlinear or complex relationships, where predictor variables are numerous or of different types, including categorical, or where the relationships studied are highly contingent. Arguably, advanced predictive methods, such as Random Forest (RF) modeling (Breiman, 2001), can provide new insights into the effectiveness of content strategies in driving engagement across SMPs, as this method handles different types of predictor variables, correlated predictors, and complex high-order interactions.

Against this background, the purpose of this study is to examine the effectiveness of SMMCS in generating engagement across different SM platforms. We divide the purpose into two research questions: 1) How does the use of SMMCS by B2B firms vary across SMPs? 2) How does the effectiveness of SMMCS to generate engagement vary across SMPs? We address these questions through an empirical study of 1700 SM messages and associated engagement data from 18 of the largest Canadian B2B companies, making three major contributions. First, we build a new SMMCS conceptualization that focuses on the function of messages and considers a broad set of targeted stakeholders. Second, we empirically demonstrate that firms use different SMMCS in different platforms. Third, we provide evidence that different SMMCS are effective in generating engagement across different platforms.

The manuscript is organized in the following manner. First, we review existing B2B social media content research to identify knowledge gaps and develop a research framework and hypotheses. Then, we outline the methodology of the study including data collection, SMMCS conceptualization, measures, and data analysis methods. The results section presents findings on the use and effectiveness of SM content strategies across SMPs in driving engagement. Finally, we conclude with theoretical and managerial contributions, limitations, and implications for future research.

## 2. Conceptual background

### 2.1. Lack of contextual SM content strategy research

Social media engagement behavior (SMEB) refers to "behavioral manifestations that have a social media focus" (Dolan et al., 2016, p.2216). It has become a key aspect of performance in B2B digital and social media marketing, as it helps build and maintain relationships, while also driving increased sales and profits (Balaji et al., 2023; Lim & Rasul, 2022). B2B marketing research has empirically studied SMEB from different viewpoints but one of the key research streams in this area focuses on understanding what kinds of contents drive engagement.

Table 1 shows that several studies have already established insights about the types of content that drive SMEB. Yet prior B2B research has not examined the use or effectiveness of SM content strategies for generating engagement across different social media platforms (SMPs). The table also illustrates that studies have used highly diverse ways of conceptualizing SMMCS to examine their effectiveness. Based on the analysis of these studies, we conclude that the extant SMMCS conceptualizations can be divided into three broad categories.

First, some studies have focused on how *SM message cues* drive SMEB, referring to the technical characteristics of message content, such as message length, text complexity, and hashtag presence (e.g., Deng et al., 2021; McShane et al., 2019). These cues influence readability and ultimately engagement. Interestingly, many message-strategy-focused studies have also used cues as supplementary predictors (see "Studied content cues" column in Table 1). Second, multiple B2B studies have examined how the *content style of SM messages,* referring to the tone of the content, influences SMEB. The choice of words can express formality or humor, such as with informative and emotional appeals (e.g., Cheng et al., 2021; Swani et al., 2017). Third, the most widely used approach to studying SMMCS focuses on the *functions of messages*, referring to the content's purpose when shared on a SMP; for example, communicating brand personality dimensions (Cortez & Ghosh Dastidar, 2022), sustainability (Yuen et al., 2023), or relationism (Sundström et al., 2020). Additional purposes include information sharing, problem solving, and public relations (Leek et al., 2019); creating awareness, building knowledge, fostering trust, generating interest, and encouraging liking, preference, conviction, or purchase intent (Juntunen et al., 2020); and delivering content such as company news, sectoral information, advertisements, corporate social responsibility (CSR) initiatives, and celebration-focused messages (Surucu-Balci et al., 2020). Other studies explore "news factors", including entertainment, prominence, significance, immediacy, unexpectedness, and human interest (Manzanaro et al., 2018).

The literature review further reveals two major gaps in extant research. First, research has solely focused on single-platform contexts to understand effective SMMCS for explaining SMEB (see "Platforms" column in Table 1). Academic research *lacks contextual understanding* of whether firms use different SMMCS across different SMPs, such as LinkedIn, Twitter, and Facebook, and whether different types of message strategies are effective in generating engagement across diverse platforms.

Second, an examination of SM content strategy conceptualizations in research indicates that, while meaningful, extant SMMCS conceptualizations consider message functions, stakeholders, and industry scope narrowly, limiting their utility for contextual explanations (see "Characteristics of conceptualization" column in Table 1). Specifically, most SMMCS conceptualizations are deductive in their nature and thus theoretically strong but focus narrowly on specific message functions that address a limited set of stakeholders (see "Considered stakeholders" column in Table 1). Many B2B social media studies have stressed the importance of creating different content for a broad range of stakeholders tailored to different platforms (e.g., Andersson & Wikström, 2017; Cartwright et al., 2021). However, content strategy studies that acknowledge stakeholders often fail to identify specific groups or focus solely on subsets, such as customers (Sundström et al., 2020), or sustainability stakeholders (Yuen et al., 2023), while overlooking others, such as employees. We argue that comparative SMMCS explanations across different platforms call for broadened conceptualizations, which cover a wide-ranging set of stakeholders. Many extant conceptualizations further concern single industry settings, delimited to specific contexts such as healthcare, shipping, or oil and gas (see "Industry scope" column in Table 1). Comparative research would benefit from generalizable SMMCS conceptualizations that cover diverse industry settings. Finally, some studies incorporate technical content cues into their analysis of message strategies. Considering cues is arguably beneficial for understanding and providing contextual explanations of SMEB.

### 2.2. Research hypotheses: the use and effectiveness of SMMCS across SM platforms

As discussed in the above section, social media message content strategy (SMMCS) research to date has focused on studying the drivers of SMEB on a single platform at a time (Pelletier et al., 2020). Little is known about whether firms employ distinct strategies across platforms, or whether these strategies are equally effective in generating

**Table 1**
Overview of key B2B studies examining how SMMCS drive SMEB.

| Study | SMMCS conceptualization | Plat-forms | Characteristics of conceptualization | | | | Data and methods | Key findings |
|---|---|---|---|---|---|---|---|---|
| | | | *Type* | *Considered stakeholders* | *Industry scope* | *Studied content cues* | | |
| Deng et al., 2021 | Cues only | Twitter | n.a. | n.a | n.a | Many, such as message length or emotional cues | Multiple linear regression analysis; 229,727 tweets; 156 brands; 10 industries | Language and visual complexity typically reduce engagement; longer messages, emotional cues, interpersonal cues, and multimodal cues enhance engagement |
| McShane et al., 2019 | Cues only | Twitter | n.a. | n.a. | Generalizable: Multi-industry context | Many, such as text difficulty and hashtags | Multiple linear regression; 2577 tweets; 48 firms; 8 industries | Fluent text and embedded image or video increase the number of likes and shares. |
| Cheng et al., 2021 | *Content style:* Informative and emotional appeals | Sina Weibo | Deductive conceptualization Message appeals | Consumers | Specific: Entertainment context | – | Negative binomial regression. 18,880 messages | Informative appeal increases likes and comments while emotional appeals increase comments and shares. |
| Manzanaro et al., 2018 | *Content function:* “news factors” characteristics of entertainment, prominence, significance, immediacy, unexpectedness, human interest. | Twitter | Deductive conceptualization Newsworthiness | Unspecific stakeholders | Generalizable: Multi-industry context | Many, such as message length and hashtags | Negative binomial regression model; 2331 tweets; 50 companies | Prominence, human interest topics, immediacy, and entertainment increases engagement as do hashtags and pictures or videos. |
| Swani et al., 2017 | *Cues:* Brand name, product name and embedded links *Content style:* Functional and emotional appeals *Content functions:* direct call to purchase | Facebook | Deductive conceptualization Motivation Theory | Fans and followers | Generalizable: Multi-industry context | Presence of brand-names, call to purchase | Bivariate Poisson Bayesian model; 326 messages; 280 firms | Direct call to purchase decreases engagement while corporate brand cue and combined functional and emotional appeal increase engagement |
| Juntunen et al., 2020 | *Content function:* creating awareness, knowledge & trust, interest, liking, preference, conviction, and purchase | Twitter | Deductive conceptualization AIDA and HoE models | Consumers and unspecific stakeholders | Generalizable: Multi-industry context | – | ANOVA; 4126 and 2811 messages; 10 firms; 5 industries | Most engaging publications employ awareness, preference, and conviction |
| Leek et al., 2016 | *Content function:* information sharing, problem solving and public relations, sales, customer endorsement, and conversation focused content | Twitter | Inductive conceptualization | Followers and unspecific stakeholders | Specific: Healthcare context | – | Negative binomial regression; 838 messages; 4 firms; 2 industries | No difference in engagement between the content functions. |
| Leek et al., 2019 | *Content function:* presence of information sharing, problem solving, and public relations focused content. | Twitter | Abductive conceptualization | Unspecific stakeholders | Specific: Healthcare context | Linguistic styles | Negative binomial regression; 838 tweets; 4 companies | Service companies' benefit of sharing information and PR vs. product companies of information about events. |
| Cortez & Ghosh Dastidar, 2022 | *Content function:* presence of brand personality dimensions of sincerity, ruggedness, excitement, competence, and sophistication | LinkedIn | Deductive conceptualization Brand personality | Customers | Specific: SME context | – | Vector autoregression (stochastic model); 211 messages | An increase in message excitement positively influences the number of likes. |
| Cortez et al., 2023 | *Content function:* presence of social, technical, and sales focused content | LinkedIn | Inductive conceptualization | Consumers and unspecific stakeholders | Specific: start-up context | – | Vector autoregression (stochastic model) of 146 messages of one company | Social messages, focusing on people or positive events, influence engagement positively. |

(*continued on next page*)

**Table 1** (*continued*)

| Study | SMMCS conceptualization | Plat-forms | Characteristics of conceptualization | | | | Data and methods | Key findings |
|---|---|---|---|---|---|---|---|---|
| | | | *Type* | *Considered stakeholders* | *Industry scope* | *Studied content cues* | | |
| Sundström et al., 2020 | *Content function:* presence of relational content functions of product-oriented, value-based, and action-oriented | LinkedIn | Deductive conceptualization Extended self | Customers | Specific: corporate gifts context | – | Experiment; 5 messages; 1 firm | Action oriented messages generate the highest engagement |
| Surucu-Balci et al., 2020 | *Content function:* presence of company news, sectoral information, advertisement, CSR, and celebration focused content. | Twitter | Inductive conceptualization | Studied strategies not stakeholder specific | Specific: container shipping context | Many, such as message length and hashtags asset | Chi-Squared Interaction Detection method; 488 tweets; 4 firms; 1 industry | CSR messages, celebration messages, reference to a tangible resource, and a higher level of vividness increase engagement. |
| Yuen et al., 2023 | *Content function:* presence of sustainability content dimensions of profit, planet and people focused content | LinkedIn | Deductive conceptualization Social Presence Theory | Sustainability related stakeholders | Specific: oil and gas context | Many, such as message length and media richness | Hierarchical regression analysis; 505 messages; 7 firms; 1 industry | Planet or people focused sustainability message strategies increase engagement. Message cues affect the effectiveness |
| *This study* | *Broadened content functions: addressing wide range of stakeholder consisting of 3 main content functions, 8 content strategies, and 31 specific strategy components* | *Multi-platform - Facebook Twitter, LinkedIn* | *A new inductive conceptualization with links to prior research* | *Broadened set of addressed stakeholders* | *Generalizable multi-industry context* | *Multiple message cues used as control variables* | *Random forest modeling; 1700 messages from 18 firms* | *Firms use different social media message content strategies across different SMPs. Different strategies are effective in diverse platforms.* |

engagement.

We build on affordance theory (Gibson, 1977; Norman, 1988) and contingency theory (Lawrence & Lorsch, 1967; Miles & Snow, 1978) to propose two general hypotheses about the use and effectiveness of SMMCS in driving SMEB across platforms, as visualized in the conceptual framework of the study (see Fig. 1).

First, affordance theory largely focuses on what the environment provides or offers (an "affordance") to an organism (Gibson, 1977). Contemporary views of affordance theory emphasize the opportunities an object provides for action, which are independent of its intended use or the user's prior knowledge, focusing instead on the potential interactions they enable for the observer (Norman, 1988). Theoretically, the affordances of social media, which can be defined as perceived "SM properties that enable and constrain specific uses of the platforms" (Ronzhyn et al., 2022, p. 14), offer meaningful justification for why firms are likely to use SMMCS differently across multiple SM platforms. Building on these ideas of affordance theory, we propose that B2B marketers likely perceive varied affordances for different types of social media, as platforms have distinct characteristics, functionalities, and audiences. For example, Facebook is a social networking site (Bitiktas & Tuna, 2020), LinkedIn a professional networking site (Cortez et al., 2023), and Twitter a microblogging site (Leek et al., 2016; Leek et al., 2019), each with distinct uses and strengths for messaging. This idea is supported by a recent qualitative case study, which found that B2B firms use SM platforms differently: Facebook served as a recruiting tool to disseminate information to a wide range of stakeholders; LinkedIn served both as a lead-generation tool targeting customers and a recruitment platform for potential employees; and Twitter functioned as a lead-generation tool while also linking to other social media platforms (Andersson & Wikström, 2017). In sum, building on affordance theory, we expect firms to use SMPs differently in their communications based on the platforms' perceived affordances.

**Hypothesis 1**. The use of SMMCS by B2B firms varies across SMPs.

The second research hypothesis builds on contingency theory, which suggests that there are no universally effective strategies (Lawrence &

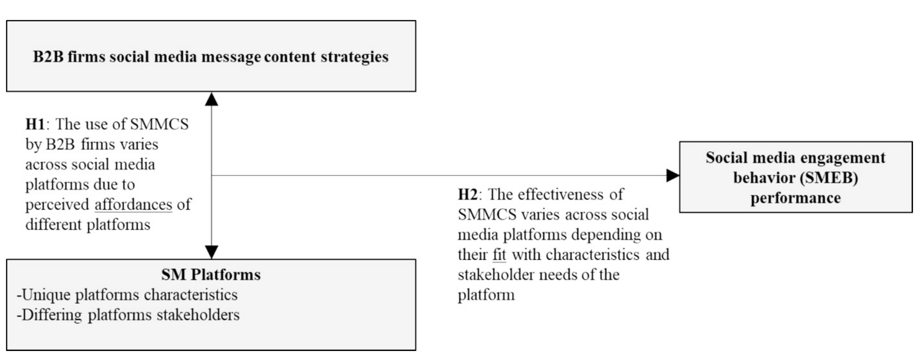


**Fig. 1.** Conceptual framework and hypotheses.

Lorsch, 1967; Miles & Snow, 1978). Instead, the effectiveness of strategies in generating engagement is contingent on their fit with the operating environment (Donaldson, 1987). Aligned with the arguments for H1, we propose that differing SMMCS are likely to drive SMEB for diverse SMPs, as they have unique characteristics and cater to distinct audiences who use these channels differently. However, we also note that the characteristics of the platforms may overlap, and therefore, some strategies could be effective for more than one platform. In sum, we hypothesize that different SMMCS lead to higher SMEB depending on their fit with the characteristics and stakeholder needs of SMPs:

**Hypothesis 2.** The effectiveness of SMMCS varies across SMPs

## 3. Study methods

### 3.1. Research design

To examine the use and effectiveness of SMMCS in generating SMEB across various SMPs, we conducted a large-scale empirical study, which builds on four steps as summarized in Fig. 2.

First, we collected a unique multi-industry SM dataset from the 18 largest Canadian B2B firms. Second, we used a qualitative coding strategy to develop a novel, broadened function-focused SMMCS conceptualization. Third, we operationalized all study variables, i.e., the independent variables (SMMCS), the dependent variables (SMEB), and the control variables (SM message cues) for hypothesis testing. Finally, we tested the proposed hypotheses using chi-square analyses, Random Forest modeling, Permutation Variable Importance (PVI) (Breiman, 2001), and the SHAP method (Lundberg & Lee, 2017).

### 3.2. Collection of multi-industry SM message dataset

To study SMMCS in the B2B context, we manually collected all SM messages from the 18 largest B2B companies in Canada over a two-month period across three SMPs: Facebook, LinkedIn, and Twitter. Firms were identified from the list of the 'top 1000' companies in Canada compiled by a reputable Canadian newspaper, The Globe and Mail. The firms represent numerous industries and, due to their size, have the resources to publish frequently on multiple platforms. The data collection occurred from September 1 to October 30, 2019, a period that allowed us to gather a substantial amount of data for advanced analyses. The three SMPs were selected because Facebook offers the largest reach among English-language platforms (Golovko & Schumann, 2019), LinkedIn is the largest professionally oriented platform with significant

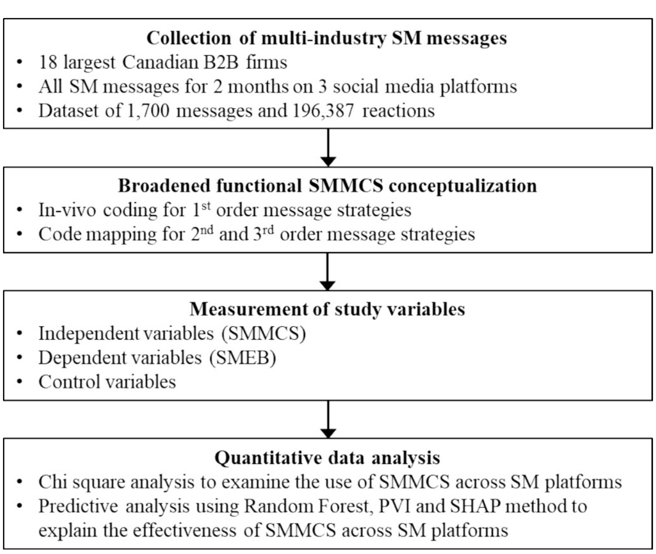


**Fig. 2.** Design of the empirical study.

**Table 2**
A summary of firms included in the study plus their SM messages in three key B2B SMP.

| Company | | Industry[1] | Rev. $ Bil. | Employees (2022) K | Number of messages | | | | Number of followers[2] | | | | Number of reactions | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | FB | LI | TW | Tot. | FB | LI | TW | Tot. | FB | LI | TW | Tot. |
| CNI | Canadian national railways | Transportation | 11 | 23 | 31 | 77 | 172 | 280 | 81,052 | 76,990 | 15,800 | 173,842 | 1700 | 6298 | 1856 | 1700 |
| MG | Magna International | Automotive parts | 40.8 | 181 | 112 | 56 | 49 | 217 | 103,315 | 320,609 | 8972 | 432,896 | 42,450 | 14,451 | 518 | 42,450 |
| SU | Suncor Energy | Oil and Gas | 29.7 | 17 | 49 | 85 | 75 | 209 | 39,241 | 267,730 | 38,200 | 345,171 | 2882 | 7082 | 763 | 2882 |
| SNC | SNC-Lavalin | Engineering | 7.5 | 36 | 56 | 59 | 72 | 187 | 62,051 | 379,080 | 22,000 | 463,131 | 2567 | 12,281 | 522 | 2567 |
| NTR | Nutrien | Agriculture | 19.6 | 25 | 51 | 34 | 59 | 144 | 6197 | 23,954 | 4030 | 34,181 | 2551 | 3977 | 437 | 2551 |
| CLS | Celestica | Technology | 6 | 26 | 46 | 30 | 62 | 138 | 4853 | 77,136 | 2111 | 84,100 | 1155 | 1982 | 247 | 1155 |
| TRP | TC Energy | Oil and Gas | 10.3 | 8 | 40 | 25 | 42 | 107 | 70,021 | 151,121 | 26,600 | 247,742 | 2241 | 2958 | 367 | 2241 |
| BBD | Bombardier | Aerospace | 16.2 | 16 | 24 | 53 | 19 | 96 | 130,635 | 527,202 | 137,600 | 795,437 | 39,879 | 22,858 | 253 | 39,879 |
| GIB | CGI | IT services | 9 | 90 | 33 | 27 | 35 | 95 | 28,183 | 479,046 | 20,100 | 527,329 | 469 | 4931 | 305 | 469 |
| ENB | Enbridge | Oil and Gas | 36.1 | 12 | 21 | 9 | 41 | 71 | 32,906 | 99,248 | 23,300 | 155,454 | 2529 | 1654 | 289 | 2529 |
| FTS | Fortis | Utilities | 6.5 | 9 | 0 | 2 | 50[3] | 2 | N/A | 2678 | N/A | 2678 | NA | 202 | 522 | 742 |
| HSE | Husky energy | Oil and Gas | 17.1 | 4 | 12 | 16 | 16 | 44 | 2308 | 120,373 | 1982 | 124,663 | 454 | 4574 | 230 | 454 |
| TECK | Teck resources | Mining | 9.7 | 12 | 11 | 15 | 18 | 44 | 17,727 | 97,743 | 12,800 | 128,270 | 747 | 2392 | 203 | 747 |
| Gold | Barrick Gold | Mining | 7.3 | 23 | 9 | 7 | 9 | 25 | 180,269 | 372,455 | 49,100 | 601,824 | 430 | 1667 | 268 | 430 |
| CVE | Cenovus Energy | Oil and Gas | 51.4 | 6 | 3 | 5 | 9 | 17 | 9577 | 102,120 | 23,800 | 135,497 | 253 | 779 | 83 | 253 |
| CNQ | Canadian natural resources | Oil and Gas | 37.4 | 10 | 0 | 1 | 14 | 15 | 40 | 129,914 | 5949 | 135,903 | NA | 101 | 53 | 154 |
| PKI | Parkland fuel | Oil and Gas | 11 | 6 | 0 | 5 | 0 | 5 | NA | 9566 | 411 | 9977 | NA | 643 | NA | 643 |
| BAM | Brookfield Asset Management | Finance | 92.7 | 203 | 0 | 4 | 0 | 4 | NA | 85,162 | NA | 85,162 | NA | 856 | NA | 856 |
| Total | | | 419.3 | 706 | 498 | 510 | 692 | 1700 | 768,375 | 3,322,127 | 392,755 | 4,483,257 | 100,307 | 89,686 | 6916 | 196,909 |

[1] Global Industry Classification Standard (GICS)
[2] Displayed on each company social media account when the data was collected.
[3] Excluded from the database since these messages were missing numbers of followers

penetration among B2B companies (Cortez et al., 2023; Sundström et al., 2020), and Twitter serves as the largest microblogging platform (Juntunen et al., 2020). This cross-industry sample provided notable diversity, as illustrated in Table 2. The dataset includes 692 (40.7 %) tweets and their 6916 reactions (3.5 %), 498 (29.3 %) Facebook messages and their 100,307 reactions (50.9 %), and 510 (30.3 %) LinkedIn messages and their 89,686 reactions (45.5 %). Web Appendix D provides full details on the distribution of the engagement data on each of these three social media platforms.

### 3.3. A novel functional SMMCS conceptualization addressing multiple stakeholders

As noted in section 2.1, the extant SMMCS conceptualizations are problematic for contextual research since they are narrow in their scope regarding message functions, covered stakeholders, and industry scope. To address the limitations, we used an inductive coding approach to build a new broader SMMCS conceptualization (Gioia et al., 2012).

We started the coding by assigning descriptive in-vivo codes to the text passages of SM messages to identify the initial first-order codes related to the purpose of the message emerging from the data. After completing the first round of coding, the lead author reviewed all codes

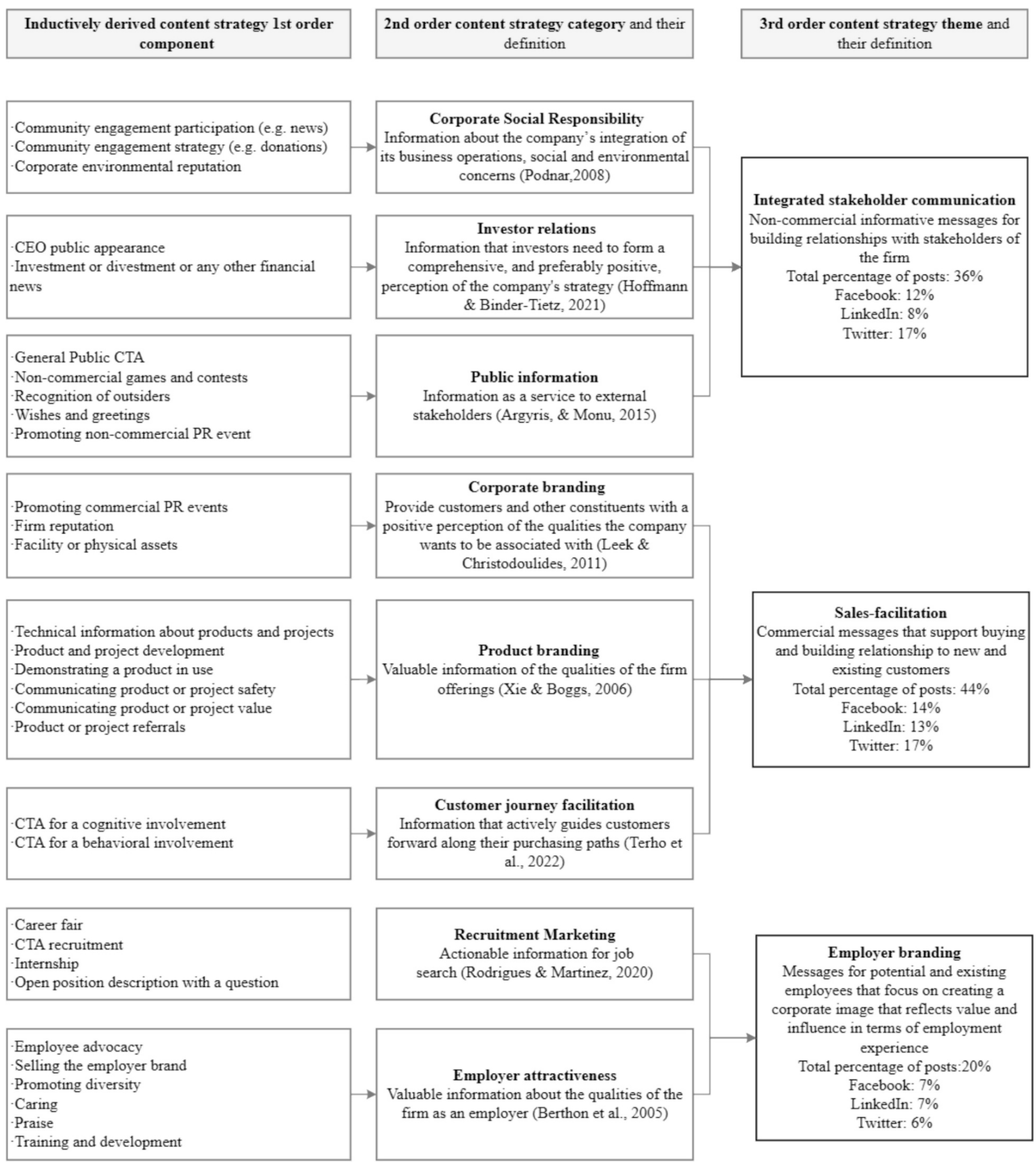


**Fig. 3.** Broadened message function-focused SMMCS conceptualization.

for consistency and established a stable codebook. Since many messages included multiple types of content strategies, they were assigned several codes, resulting in 2656 code occurrences, with an average of 1.56 codes per message.

This coding process led to the identification of 31 first-order codes, as summarized in Fig. 3. Web Appendix A provides examples of messages for the final first-order content strategy coding. Since the 31 first-order message strategies were too detailed to be effectively used in predictive analysis, given the sample size, two authors performed code mapping (Anfara Jr., 2008). In this process, the initial codes were organized into eight second-order categories which in turn were grouped into three abstract third-order dimensions through iterations, resulting in a more theoretical structure. We followed Miles and Huberman (1984, p.27), who recommend counting occurrences, noting themes arising from patterns, and "making conceptual/theoretical coherence." Fig. 3 summarizes the final conceptualization, including the inductively derived first-order codes, as well as the more abstract second- and third-order dimensions, with construct definitions and references.

Notably, the final third-order dimensions of SMMCS align closely with Cartwright et al.'s (2021) prior review study, which distinguished three main uses of social media in B2B (integrated communication, sales facilitation, and employee engagement), providing support for the theoretical relevance of the conceptualization. Our second-order codes highlight content categories that were previously overlooked in the SMMCS research, such as employer attractiveness and investor relations (see Table 1). As expected, many second-order codes also align with findings from previous studies, such as corporate social responsibility (Yuen et al., 2023) and customer journey facilitation (Swani et al., 2017).

### 3.4. Measurement of SMMCS, SMEB and control variables

We measure the SMMCS following the qualitative conceptualization work discussed in detail in the previous Section 3.3. Each of the 31 first-order SMMCS codes (i.e., variables) takes the value of one if the message function includes the specific components of the content strategy it represents, and zero otherwise. Each second- or third-order SMMCS code takes the value of one if the message function includes components of at least one of its nested first-order SMMCS, and zero otherwise. More precisely, a given SMMCS, whether it is of first-, second-, or third-order, is either present in a message (and the correspondent code takes the value of 1) or absent (and the correspondent code takes the value of 0).

In turn, SMEB has been operationalized in many ways in academic research, either by adding the number of reactions and shares (Manzanaro et al., 2018; McShane et al., 2019), the number of reactions and comments (Swani et al., 2017; Yuen et al., 2023), by adding the number of likes, shares, and comments (Cheng et al., 2021; Deng et al., 2021; Leek et al., 2019; Surucu-Balci et al., 2020) or even by incorporating more variables like video views (Juntunen et al., 2020) or impressions, and clicks (Cortez et al., 2023; Cortez & Ghosh Dastidar, 2022; Sundström et al., 2020). We measure SMEB based on the number of platform-specific standard reactions to each firm's messages. We chose this approach since these reactions arguably reflect well the overall engagement level, being the key measurement variable virtually in all SMEB research, and this information is equally available in all studied platforms, whereas other engagement data such as the number of shares per post (e.g. LinkedIn) might not be available in all studied platforms. We used the schema outlined in Table 3, since the standard reaction types differ between SMPs.

**Table 3**
The measurement of SMEB based on the reactions of SM messages.

| SM platform | Twitter | Facebook | LinkedIn |
|---|---|---|---|
| SMEB operationalization | love | love + like + haha + wow + sad + angry | love + like + celebrate + insightful + curious |

Web Appendix D provides details on the distribution of the number of reactions. We compute the behavioral reaction levels (i.e., high or low) to measure SMEB, using the platform-specific sample datasets. This approach allows us to distinguish between high-engagement messages and low-engagement messages, based on whether their number of reactions is above or below their SMP median reactions level. As such, we create a binary SMEB variable that takes the value of one for high behavioral reactions and zero otherwise. This SMEB measurement approach is chosen due to the variability of engagement across SMPs and the robustness of the median, which remains unaffected by extreme values. Additionally, this study focuses on global effects, i.e., understanding a message's engagement level in comparison to the absolute engagement level of its SMP, rather than its relative, company-specific engagement level.

We include several control variables: message origin (Origin: Shared (the firm shares a message from another source) vs. Original (the firm creates its own message)), media richness (Media richness: 1. Video & text, 2. Image & text, 3. Text only), number of followers (Followers: Low vs. High), number of messages published on the company page of the social network during the data collection (Messages: Low vs. High), and message length based on character count (Message length: Short vs. Long).

The binary control variables take the value zero if a message falls into the first category and one otherwise. For the variables Followers and Messages, the category "High" indicates that the company's number of followers or messages on the SMP is higher than the platform's sample median. Thus, Followers and Messages distinguish between messages from companies with high-posting rates or many followers, and those with low-posting rates or fewer followers on a given SMP. The company's number of followers on each SMP is obtained from its corporate page. Followers' sample median value equals 62,051 on Facebook, 267,730 on LinkedIn, and 15,800 on Twitter. The number of messages a company has posted on a given SMP during the data collection equals the size of its sample on this platform. Messages' sample median value equals 49 on Facebook, 56 on LinkedIn, and 62 on Twitter. The control variable Message length distinguishes between long posts with more characters than the SMP's sample median value and short posts with fewer or equal characters. Message length sample median value equals 267 on Facebook, 278 on LinkedIn, and 202 on Twitter. Web Appendix D provides details on the distributions of Followers, Messages, and Message length before their binarization.

### 3.5. Quantitative data analysis

The first hypothesis proposes that SMMCS use differs across SMPs. We use crosstabs and Pearson chi-square analyses to test the hypothesis by examining the distribution of the eight second-order SMMCS variables across the three studied SMPs.

The second hypothesis suggests that different types of SMMCS are effective in generating SMEB across SMPs. We employ Random Forest (RF) modeling to analyze effective content strategies in each studied SMP, using second-order SMMCS categories to achieve a meaningful level of detail in the results. RF offers several advantages over traditional regression-based methods, as it can more effectively handle numerous categorical predictors, account for correlated predictors, and manage complex high-order interactions. It is also more accurate than individual decision trees (De Caigny et al., 2021; Gattermann-Itschert & Thonemann, 2022). RF also enables the assessment of variable importance, providing insight into how predictors contribute to model performance (Breiman, 2001).

Before fitting the three RF models, each platform's data were equally partitioned into training and test datasets (see Table 4 for details). We use a hyperparameter tuning strategy based on a full cartesian grid search. The grid and the best hyperparameter combination used to fit each RF model are shown in Tables B1 and B2 in Web Appendix B, with further details. The predictive performance of each final RF model was

**Table 4**
Low- and high-engagement messages in train and test data sets by platform.

| Dataset | Twitter | | | Facebook | | | LinkedIn | | |
|---|---|---|---|---|---|---|---|---|---|
| SMEB | *Low* | *High* | *Tot.* | *Low* | *High* | *Tot.* | *Low* | *High* | *Tot.* |
| Training sample | 180 | 166 | 346 | 126 | 123 | 249 | 129 | 127 | 256 |
| | 52.0 % | 48.0 % | 50.0 % | 50.6 % | 49.4 % | 50.0 % | 50.4 % | 49.6 % | 50.2 % |
| Test sample | 180 | 166 | 346 | 126 | 123 | 249 | 128 | 126 | 254 |
| | 52.0 % | 48.0 % | 50.0 % | 50.6 % | 49.4 % | 50.0 % | 50.4 % | 49.6 % | 49.8 % |
| Full sample | 360 | 332 | 692 | 252 | 246 | 498 | 257 | 253 | 510 |
| | 52.0 % | 48.0 % | 100.0 % | 50.6 % | 49.4 % | 100.0 % | 50.4 % | 49.6 % | 100.0 % |

Note. Low = low engagement messages; High = high engagement messages.

then assessed using its corresponding test data and five commonly applied metrics: recall, precision, F1 score, accuracy, and area under the curve (ROC-AUC) (see Biecek & Burzykowski, 2021). The metrics indicate that the final RF models reported in our study have good predictive performance (see Web Appendix C for full details).

We complement the RF analyses with Permutation Variable Importance (PVI) (Breiman, 2001) and Altmann et al. (2010) procedures for assessing the importance of the predictors in each RF model and its statistical significance respectively. A predictor's PVI equals the average decrease in model predictive performance after randomly permuting its values across all the individual trees in the forest. A significant drop in model performance indicates that the predictor is important. Altmann's method provides *p*-values for each predictor's PVI score.

Finally, to provide more detailed insights into the nature of significant relationships between SMMCS and SMEB, we augment the analysis with the SHAP method (Lundberg & Lee, 2017), using the R package fastshap to compute the Shapley value of each message per predictor (Shapley, 1953).

We report SHAP summary and dependence plots in the results. First, the SHAP summary plots help examine the directionality of significant relationships between SMMCS and SMEB. On the SHAP summary plot, predictors are ordered according to their SHAP Variable Importance (SVI) score (i.e., their mean absolute Shapley value across the training data), and each point represents the SHA*P* value for a specific predictor-message pair, with the color indicating the predictor value. The message position on the horizontal axis of SHAP summary plots represents a Shapley-based predictor contribution to the difference between the message's actual prediction (i.e., its high SMEB predicted probability) and the baseline (i.e., average training prediction). A positive SHAP value indicates that a predictor value has a positive impact on high SMEB predicted probability (i.e., pushing the message's high SMEB predicted probability above the baseline), whereas a negative SHAP value indicates that a predictor value has a negative impact on high SMEB predicted probability (i.e., pushing the message's high SMEB predicted probability below the baseline). Second, the SHAP dependence plots further identify interaction effects when summary plot analyses indicate the presence of unclear, varying effects.

## 4. Study results

### 4.1. The use of SMMCS across different social media platforms

We start the results section by examining whether B2B firms use SMMCS differently across the three studied social media platforms (SMPs). Table 5 summarizes the second-order content strategies across the three SMPs, based on crosstabs and Pearson chi-square tests (see Web Appendix E for control variables results).

Notably, we find that three quarters (75 %) of the bivariate relationships between the second-order content strategies and SMPs are statistically significant (*p*-value ≤1 %), indicating that firms use some content strategies differently across the three platforms.

Messages on Facebook most frequently include content related to Public Information, such as encouraging people to read safety guidelines around railroad tracks or promoting non-commercial events like a chamber of commerce gathering. Another popular use of Facebook is promoting Employer Attractiveness. This includes employees sharing their work experiences, promoting the employer brand, and demonstrating how the company cares for its workforce. Public Information

**Table 5**
SMMCS use across Twitter, Facebook, and LinkedIn.

| SMMCS | | TW | FB | LI | Tot. | χ2 Square | P value | Sig. |
|---|---|---|---|---|---|---|---|---|
| Integrated stakeholder communication | | | | | | | | |
| 1. CSR communication | % | 29 % | 27 % | 20 % | 25 % | 13.26 | 0.001 | ** |
| | *n* | 198 | 133 | 100 | 431 | | | |
| 2. Investor relations | % | 11 % | 5 % | 9 % | 9 % | 15.29 | 0.001 | ** |
| | *n* | 78 | 24 | 45 | 147 | | | |
| 3. Public information | % | 24 % | 30 % | 11 % | 22 % | 55.03 | 0.000 | ** |
| | *n* | 165 | 151 | 58 | 374 | | | |
| Sales facilitation | | | | | | | | |
| 4. Corporate branding | % | 28 % | 30 % | 26 % | 28 % | 1.67 | 0.433 | n.s. |
| | *n* | 195 | 148 | 133 | 476 | | | |
| 5. Product branding | % | 16 % | 20 % | 24 % | 20 % | 11.85 | 0.003 | ** |
| | *n* | 113 | 102 | 124 | 339 | | | |
| 6. Customer journey facilitation | % | 22 % | 23 % | 18 % | 21 % | 4.05 | 0.132 | n.s. |
| | *n* | 151 | 117 | 94 | 362 | | | |
| Employee engagement | | | | | | | | |
| 7. Recruitment Marketing | % | 12 % | 12 % | 19 % | 14 % | 13.00 | 0.002 | ** |
| | *n* | 82 | 61 | 95 | 238 | | | |
| 8. Employer attractiveness | % | 11 % | 25 % | 18 % | 17 % | 41.79 | 0.000 | ** |
| | *n* | 74 | 124 | 91 | 289 | | | |
| *Total* | | 692 | 498 | 510 | 1700 | | | |

Note. ** *p*<. 01; * p<. 05; +p<. 10, n.s. not significant.
TW: Twitter, FB: Facebook, LI: LinkedIn, χ2: Chi-square.

messages are more frequently published on Facebook than on Twitter or LinkedIn. Not surprisingly, Facebook is not the platform of choice for Investor Relations.

LinkedIn is the platform of choice over the other two for recruitment marketing content. On the other hand, LinkedIn is the least frequently used to publish content related to CSR. This could be because firms prefer to reach a wider range of stakeholders on Facebook for this kind of news, which may also explain why LinkedIn is the least used for Public Information. As expected, our results show that LinkedIn is the most used for product branding.

Finally, Twitter resembles Facebook in terms of the content types that are least often used on LinkedIn, and it is like LinkedIn in content types that are least often used on Facebook. In other words, no specific content type uniquely distinguishes tweets.

In summary, the empirical findings reveal systematic and statistically significant differences in some SMMCS across the platforms although we also observe some similarities in platform usage, such as Recruitment Marketing on Twitter and Facebook. We conclude that the results provide support for *Hypothesis 1: The use of SMMCS by B2B firms varies across SMPs*.

### *4.2. The effectiveness of SMMCS to drive SMEB across social media platforms*

We use predictive RF modeling and variable importance analysis for testing the hypothesis concerning the effectiveness of different SMMCS in deriving SMEB across different social media platforms (SMPs). Importantly, the RF model showed good predictive performance based on the established criteria: recall, precision, F1 score, accuracy, and AUC, as explained in detail in Section 3.5 and Web Appendix C, thus providing support for the predictive validity of the model. Table 6 presents the PVI raw scores, produced by the platforms' RF models, along with their associated *p*-value estimates based on Altmann et al.'s (2010) method. The PVI raw score reflects the variable importance in predicting SMEB. A predictor is significantly important in predicting SMEB level if its raw score is close to 1 % or higher and its associated p-value is ≤5 % (see Altmann et al., 2010). The RF findings indicate that each SMP has a distinct subset and ranking of significantly important predictors, as summarized in Table 6 below.

**Table 6**
PVI raw scores and associated *p*-values.

| Variable | Twitter | | Facebook | | LinkedIn | |
|---|---|---|---|---|---|---|
| | *Score* | *p-value* | *Score* | *p-value* | *Score* | *p-value* |
| Content Strategy | | | | | | |
| Integrated stakeholder communication | | | | | | |
| 1. CSR communication | 0.02* | 0.02 | 0.01+ | 0.09 | 0.01 | 0.17 |
| 2. Investor relations | 0.01* | 0.01 | 0.01* | 0.01 | 0.01* | 0.05 |
| 3. Public information | 0.00 | 0.30 | 0.01* | 0.01 | 0.00 | 0.44 |
| Sales facilitation | | | | | | |
| 4. Corporate branding | 0.00 | 0.25 | 0.00 | 0.40 | 0.01 | 0.12 |
| 5. Product branding | 0.01+ | 0.06 | 0.00 | 0.26 | 0.01 | 0.19 |
| 6. Customer journey | 0.03** | 0.00 | 0.02** | 0.00 | 0.02* | 0.03 |
| Employee engagement | | | | | | |
| 7. Recruitment marketing | 0.02* | 0.01 | 0.00 | 0.42 | 0.03** | 0.00 |
| 8. Employer attractive. | 0.00 | 0.46 | 0.01* | 0.04 | 0.00 | 0.39 |
| Control | | | | | | |
| Origin | 0.00 | 0.11 | 0.01* | 0.03 | 0.00 | 0.30 |
| Media richness | 0.04** | 0.00 | 0.01+ | 0.05 | 0.02* | 0.01 |
| Followers | 0.00 | 0.20 | 0.11** | 0.00 | 0.07** | 0.00 |
| Messages | 0.02* | 0.01 | 0.02** | 0.00 | 0.11** | 0.00 |
| Message length | 0.00 | 0.32 | 0.00 | 0.31 | 0.00 | 0.41 |

Note. p-value estimates are based on the method of Altmann et al. (2010).
** *p*<. 01; * p<. 05; +p<. 10, n.s. not significant.

Notably, the findings show that only two SMMCS (Customer Journey and Investor Relations) and one control variable (Messages) are significantly important in predicting SMEB level across all three platforms, although their ranking differs. Additionally, three SMMCS and one control variable are important in predicting SMEB level for only one platform: CSR Communication for Twitter, and Public Information, Employer Attractiveness, and Origin for Facebook.

Since the Random Forest models' PVI raw scores and their statistical significance do not give information about the nature (sign) of a predictor effect (impact) on high SMEB probability, i.e., whether it is a pure positive effect, a pure negative effect, or a varying effect, we complement the analysis with SHAP summary plots. These analyses provide further details about the impact of the studied variables on the probability of high engagement, as outlined in Section 3.5. The SHAP summary plots (Figs. 4a, 4b, and 4c) help visualize and interpret the nature of significant SMMCS effects.

The SHAP summary plots show that significant SMMCS have either a purely positive effect, a purely negative effect, or an unclear varying effect on SMEB. A content strategy with a purely positive effect (i.e., positive relationship with SMEB) implies that this type of content increases high SMEB probability. This is the case, for example, with CSR Communication on Twitter (see Fig. 4a). On the other hand, a content strategy with a purely negative effect (i.e., negative relationship with SMEB) implies that this type of content decreases high SMEB probability. This is the case, for example, with Customer Journey on Twitter (see Fig. 4a). Finally, a content strategy with a varying effect on SMEB may have a positive or negative impact depending on external conditions. This is the case, for example, with Public Information on Facebook (see Fig. 4b). To more closely assess these unclear varying effects, we conduct post-hoc analysis based on an interaction heuristic and SHAP dependence plots with interaction visualization to detect the conditions under which the positive relationships occur (see Figs. 5a and 5b).

First, Fig. 4a shows SHAP summary plot results for Twitter. Three content strategies have positive effects on high SMEB probability in Twitter (i.e., messages with these types of contents are more likely to derive high SMEB than messages without these types of contents). Specifically, CSR Communication, Investor Relations, and Employer Attractiveness impact engagement positively with SVI values of 4.03 %, 3.53 %, and 1.20 %, respectively. In turn, Customer Journey Facilitation and Recruitment Marketing have negative effects on high SMEB probability (i.e., messages with these types of contents are less likely to derive high SMEB than messages without these types of contents), with SVI values of 3.44 % and 2.62 %, respectively.

Fig. 4b shows SHAP summary plot results for Facebook. In this context, Customer Journey Facilitation has a significant negative effect on high SMEB probability, while Investor Relations has a significant positive effect on high SMEB probability, with SVI values of 2.90 % and 1.40 % respectively (see Fig. 4b). In turn, Public Information and Employer Attractiveness show unclear, varying effect directions, suggesting potential interaction effects, with SVI values of 1.90 % and 1.00 %, respectively. SHAP dependence plots confirm interactions, since the effect of Public Information on high SMEB probability is mainly positive for messages that also belong to the Customer Journey Facilitation category but mainly negative for those that do not fall into this category (see left-hand side of Fig. 5a). As for Employer Attractiveness, its effect on high SMEB probability is mainly positive for original messages but mainly negative for shared ones (see right-hand side of Fig. 5a).

Fig. 4c shows SHAP summary plot results for LinkedIn. In this context, Recruitment Marketing has a negative effect on high SMEB probability, while Investor Relations has a positive effect on high SMEB probability, with SVI values of 6.20 % and 3.50 %, respectively. In turn, Customer Journey Facilitation exhibits a varying effect, with an SVI value of 2.70 % suggesting potential interaction effects. The SHAP dependence plot confirms interaction as the effect of Customer Journey

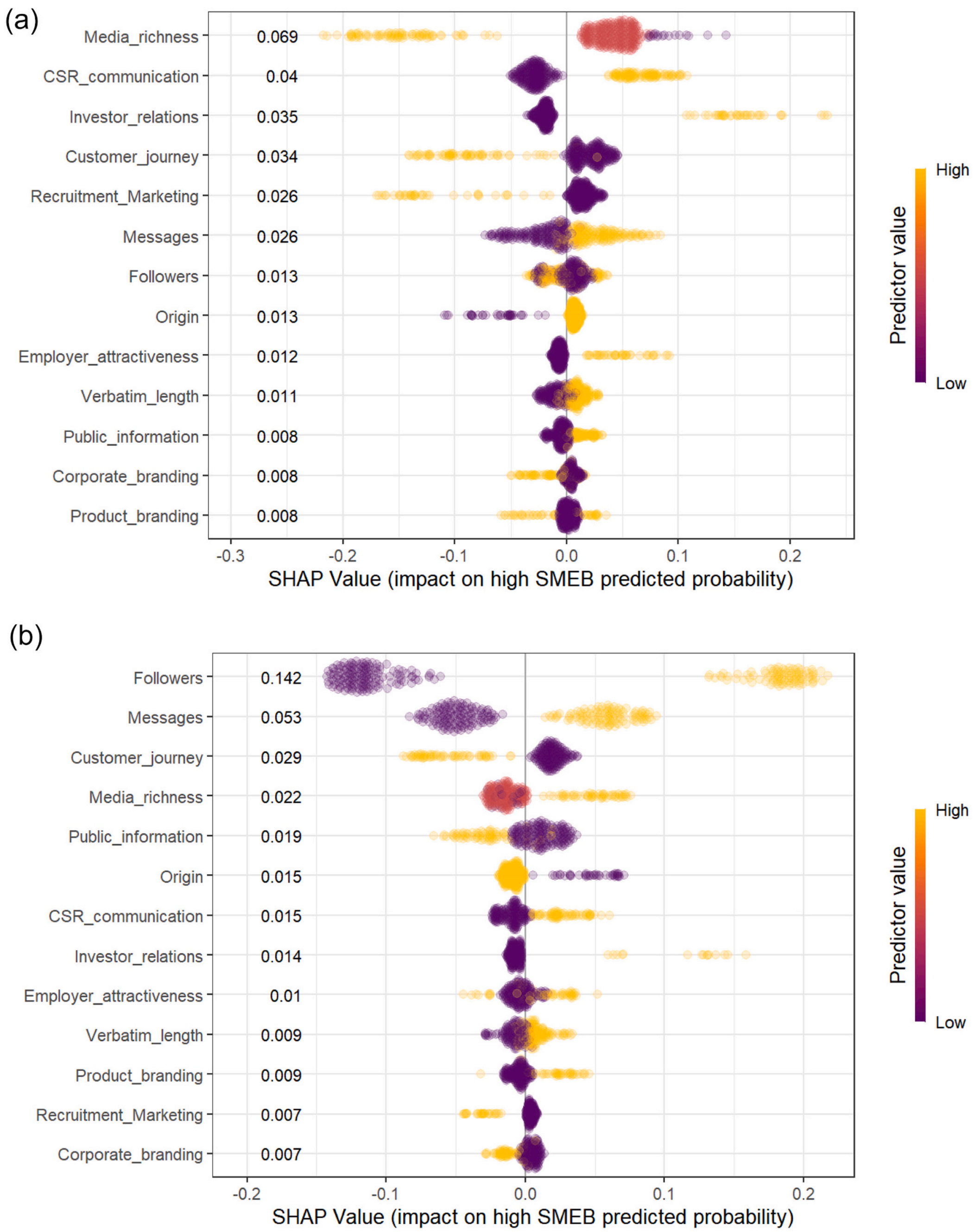


**Fig. 4.** a: Twitter SHAP summary plot.
Note. On SHAP summary plots, *predictors are ordered according to their SVI, and each point represents the SHAP value for one specific predictor and a message, with the color indicating the predictor value so that yellow indicates largest values and purple smallest values. For any SMMCS predictor, yellow points represent messages that belong to it while purple points represent messages that do not belong to it. For the binary control variables Messages, Followers, Message length, Origin, yellow points represent messages that belong to High/Long/Original categories* (i.e. *Messages/Followers/ Message length /Origin equal 1), while purple points represent messages that belong to Low/Short/Shared categories (*i.e. *Messages/Followers/Message length/Origin equal 0). For the categorical control variable Media richness, yellow points represent text only messages, red points represent image & text messages, and purple points represent video & text messages.*
b: Facebook SHAP summary plot (See Fig. 4a note above).
c: LinkedIn SHAP summary plot (See Fig. 4a note above).

Facilitation on high SMEB probability is mainly positive for messages from high-posting companies and mainly negative for those from low-posting companies (see Fig. 5b).

Table 7 summarizes the findings discussed above. While the analysis has been conducted at second-order content strategy level, we note that all three third-order SMMCS dimensions—Integrated Stakeholder Communication (CSR communication, Investor relations and Public information), Sales Facilitation (Customer Journey), and Employer Branding (Recruitment marketing and Employer Attractiveness)—are significantly represented on two SMPs, Twitter and LinkedIn through at least one of their second-order components, while Sales Facilitation is the only third-order dimension not present on Facebook (see Table 7).

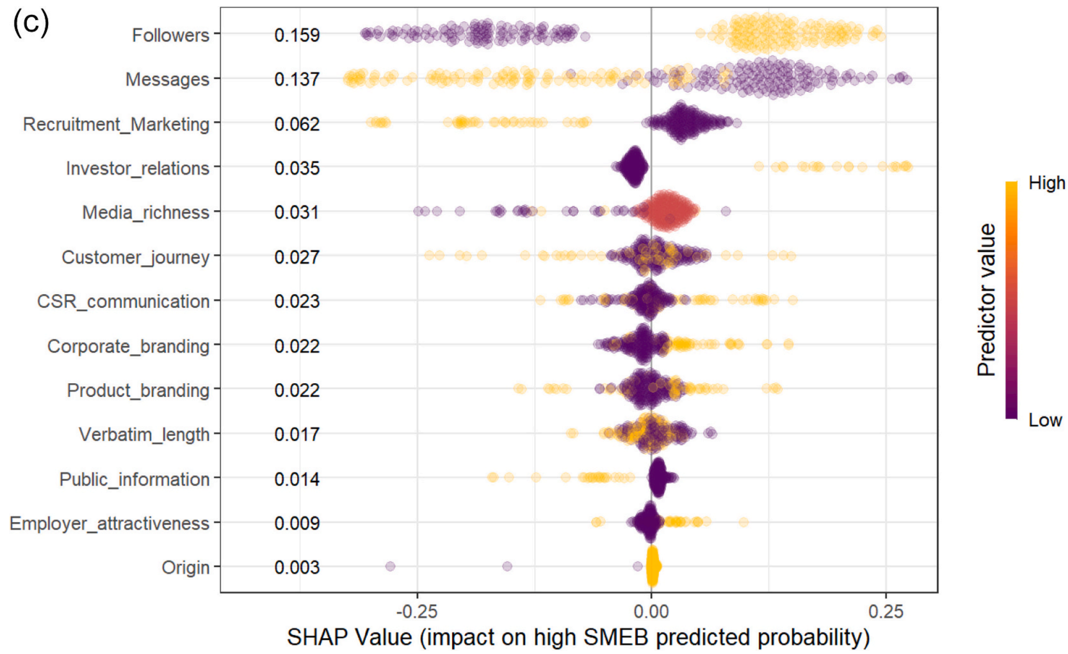


**Fig. 4.** (*continued*).

*Moderating effects: the positive impact on high SMEB probability is pending on* [a] *journey facilitation;* [b] *high posting firm;* [c] *original messages;* [d] *journey facilitation;* [e] *high posting firm for Image & text messages.*

More precisely, integrated stakeholder communication is represented by Investor Relations on the three SMPs, CSR communications on Twitter, and Public Information on Facebook. Sales facilitation is represented by the customer journey on the three SMPs, and Employer Branding is represented by recruitment marketing on the three SMPs. However, the SMMCS types behave very differently across the platforms.

In contrast to Leek et al. (2016), who found no differences in engagement between content strategies on Twitter, our results indicate that only certain SMMCS are effective on this platform, while others result in negative outcomes. We expect that this difference is due to the expanded SMMCS conceptualization, which takes into account a wider set of stakeholders and message strategy functions. Specifically, the findings show that Twitter, as a microblogging platform with a short message format, favors "stakeholder communication"-focused SMMCS targeting a broad set of stakeholders, as evidenced by effective CSR and investor communications-focused SMMCS. These findings align with prior research by Surucu-Balci et al. (2020) that CSR Communication focused message strategies drive high SMEB. Additionally, our results extend prior findings by showing that sales and recruitment-focused SMMCS perform poorly in this context, as Customer Journey Facilitation and Recruitment Marketing contents have negative effects on high SMEB probability.

In turn, Facebook, as a social engagement platform, shows positive SMMCS for Investor Relations as well as conditional positive effects for Public Information and Employer Attractiveness, pending on having a guiding tone (Public Information) or being original messages (Employer Attractiveness) respectively. Thus, the effective messages here fall into "stakeholder communications" or "employer branding." In turn, the purely "sales-focused" Customer Journey Facilitation SMMCS alone, has a negative impact on high SMEB probability in Facebook. This finding aligns with the results of the exclusively Facebook-focused content strategy study by Swani et al. (2017), which found that direct calls to purchase tend to decrease engagement in this context and that firms are better off using informative message strategies.

LinkedIn, as a professional networking platform, is the only platform where sales-focused communications content has a positive impact on high-engagement probability. This finding aligns with Sundström et al. (2020) who found that action-oriented messages in this platform are connected to high engagement. However, this positive effect of Customer Journey Facilitation-focused message content depended on a systematic approach to social media marketing, as demonstrated by a high-posting firm. Our results further indicate that the probability of high engagement on LinkedIn increases with Investor Relations-focused content but decreases with recruitment marketing content. Finally, prior studies that have highlighted the relevance of social and sustainability-focused messages on LinkedIn have found that social messages (Cortez et al., 2023) and sustainability-related messages, about people or the planet (Yuen et al., 2023), positively drive engagement. We did not find support for these notions but conclude that direct comparison is difficult due to differing message strategy conceptualizations across studies.

Finally, an analysis of significant cues highlights that a systematic approach to social publishing is central for driving SMEB in the B2B context (high posting-see Table 6), as the number of followers, and media richness for high-posting firms are positively connected to SMEB. This finding aligns with Karampela et al.'s (2020) notion that SM presence positively influences commitment and satisfaction in buyer-seller relationships.

Based on the above findings, we conclude that there is support for *Hypothesis 2: The effectiveness of specific SMMCS varies across SMPs depending on their fit with characteristics and stakeholder needs of the platform.*

## 5. Conclusions

### 5.1. Theoretical implications

Numerous academic studies have offered insights into what types of SM cues and message content generate high engagement in the B2B context. However, extant research lacks deeper insight into whether and how firms should tailor their message content strategies across different SMPs. This study extends research in this area by examining whether firms use different functional SMMCS across platforms and whether the effectiveness of specific SMMCS varies in driving engagement across SMPs. The findings of the study offer three substantial theoretical

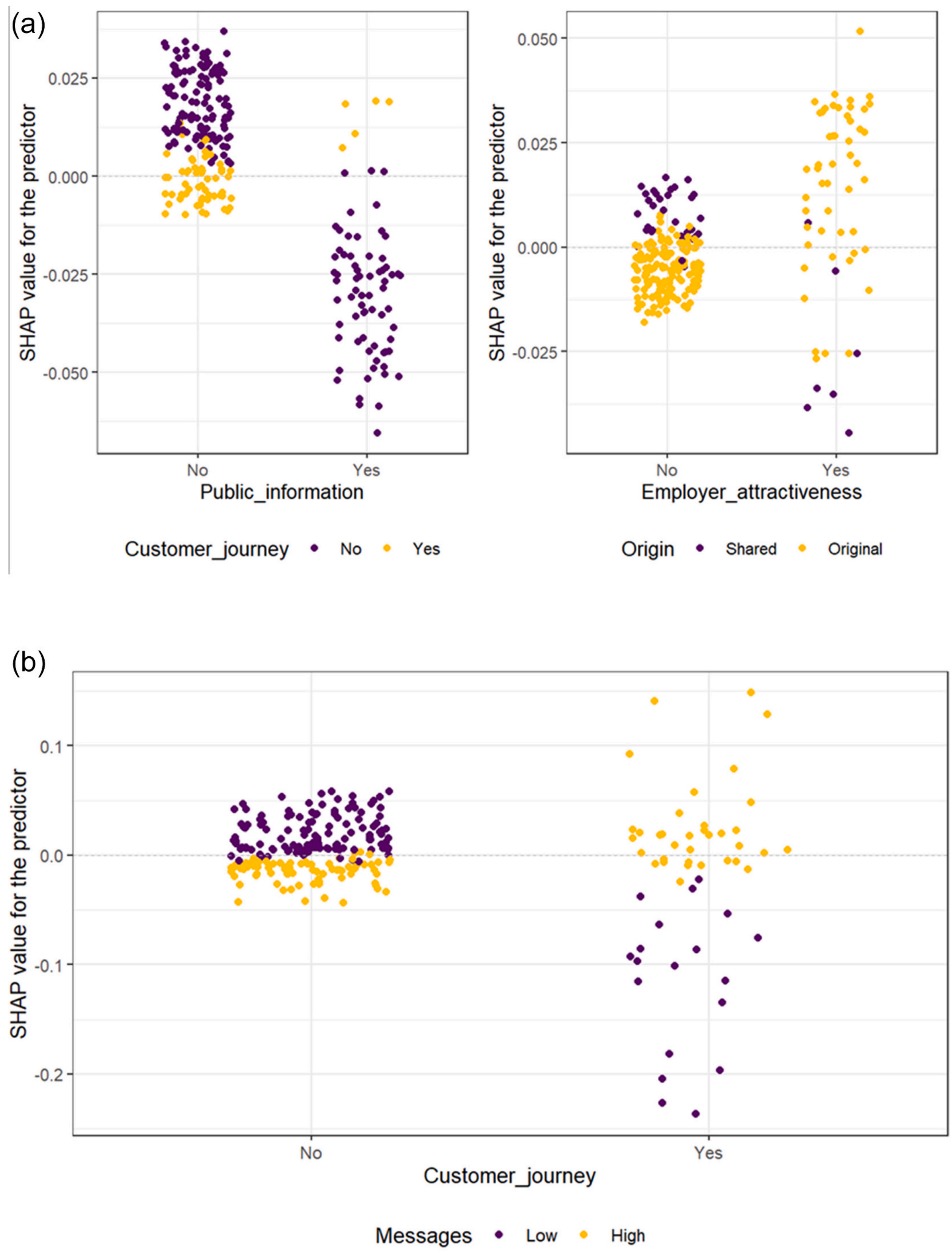


**Fig. 5.** a: Facebook SHAP dependence plots with interaction visualization.
b: LinkedIn SHAP dependence plot with interaction visualization.

contributions to B2B social media marketing research.

First, a review of SMEB research indicated that existing functional SMMCS conceptualizations are problematic for contextual explanations, as they are narrow in scope regarding message functions, covered stakeholders, and industry range. This is due to the nature of deductive theory-based conceptualizations that tend to delimit their view on specific theory-focused aspects of messages, leading to narrow views of message functions (c.f. Juntunen et al., 2020; Manzanaro et al., 2018; Sundström et al., 2020; Yuen et al., 2023). In turn, the existing inductive conceptualization (see Cortez et al., 2023; Leek et al., 2016; Surucu-Balci et al., 2020) has focused on single-industry-specific message strategies and a narrow set of stakeholders. This study contributes by developing a broadened SMMCS conceptualization comprising 31 detailed SMMCS, grouped into eight second-order categories and three third-order dimensions. The conceptualization is based on data from firms in multiple industries and SMPs providing a broad and a comprehensive view on message strategy functions across different contexts. Importantly, the novel conceptualization broadens prior SMMCS conceptualizations in terms of considered stakeholders, such as investors and employees, who have been largely ignored by prior studies analyzing B2B firms' social media publications, making it well suited for research focused on contextual explanations.

Second, prior B2B marketing studies on social media message strategies have heavily focused on single-platform contexts, and little is

**Table 7**
Summary of key SMMCS predictors of SMEB.

| Variable | Twitter | Facebook | LinkedIn |
|---|---|---|---|
| Content Strategy | Customer journey –<br>Recruitment marketing –<br>CSR communication + *<br>Investor relations + | Customer journey –<br>Public information +/− * [a]<br>Employer attractiveness +/− * [c]<br>Investor relations + | Recruitment marketing –<br>Customer journey +/− [b]<br>Investor relations + |
| Control | Media richness –<br>Messages + | Followers +<br>Messages +<br>Origin – * | Messages +/− [d]<br>Followers +<br>Media richness +/− [e] |

Notes: SMMCS and control variables listed based on their importance in predicting SMEB level based on PVI method. The directionality of a predictor's effect on high SMEB probability, based on SHAP method: + Purely positive effect; − Purely negative effect; +/− Varying effect.
* Predictor is important in predicting SMEB level only for one platform.

known about how firms use SMMCS across different social media platforms. Building on ideas put forward in affordance theory (Gibson, 1977; Norman, 1988), this study demonstrates that firms use SMMCS differently across various platforms with unique characteristics and audiences, while some similarities are observed. We find empirical support for the idea that the perceived properties of platforms drive or constrain their utilization, resulting in distinct "Facebook affordances", "Twitter affordances", or "LinkedIn affordances" (see Ronzhyn et al., 2022), which lead to varying use of SMMCS across SMPs. To our knowledge, prior comparative research on the differential use of SMMCS across platforms has been either limited to consumer settings exploring SMP purposes with survey data (see Pelletier et al., 2020), or to qualitative case research in the B2B context with a handful of firms (Andersson & Wikström, 2017). Our study confirms these ideas based on real-world large-scale B2B social media dataset from multiple industries. Our findings largely align with Andersson and Wikström's (2017) qualitative insights in the B2B context, which point out that firms use LinkedIn as a recruitment tool and Facebook for Public Information, CSR Communication, and Employer Branding.

Third, all explanatory SMEB focused B2B social media content strategy studies to date have been conducted in single social media platform contexts. Thus, research on the effectiveness of different SMMCS across SM platforms has been limited to isolated findings on specific platforms, and comparative studies in the B2B context have been entirely lacking. This study bridges the B2B social media marketing knowledge gap by empirically confirming a contingency theory-based hypothesis (see Lawrence & Lorsch, 1967; Miles & Snow, 1978) that the effectiveness of SMMCS varies across platforms depending on their fit with platform characteristics (see Donaldson, 1987). Interestingly, we found that some strategies were effective across multiple platforms, suggesting that different platform characteristics are not entirely exclusive. With this approach, the results provide rich novel insights on how effective SMMCS strategies differ across the three studied platforms, mostly aligning with prior single-platform focused research findings - as discussed in detail in the results section. Overall, the findings indicate that Twitter favors "stakeholder communications"-focused SMMCS, including CSR and investor relation communications, but undermines sales- and recruitment-focused SMMCS (c.f. Surucu-Balci et al., 2020). Facebook, in turn, shows positive SMEB effects for "stakeholder communications" and "employer branding" focused content strategies but negative effects for sales focused SMMCS (c.f. Swani et al., 2017). In LinkedIn, the sales-focused customer journey message strategies (i.e., true only for messages from firms with a high-posting frequency) (c.f. Sundström et al., 2020) and Investor Relations-focused SMMCS are positively related to SMEB in contrast to recruitment-focused SMMCS with negative effects. Thus, the findings of this research indicate that firms can achieve higher engagement by strategically tailoring their social media message content strategies to platforms' characteristics and stakeholders.

### 5.2. Managerial implications

Our study offers practical guidelines for SM managers who wish to increase engagement with stakeholders across different SMPs. To this effect, Table 7 offers a playbook for those managers who wish to increase engagement or to avoid decreasing engagement. Generally, our findings highlight that firms should adapt SMMCS to different SMPs, as their effectiveness to drive SMEB depends on their fit with the platforms. Therefore, cross-posting—publishing the same content across different platforms—should be approached carefully. While some topics, such as Investor Relations, can generate engagement across all three social media platforms, other types of content should be restricted to specific platforms when a firm's goal is to maximize engagement. Our results show that a given message category may decrease the likelihood that the message generates a level of engagement higher than the median level on one platform while it may increase that likelihood on another platform. For example, Customer Journey Facilitation decreases the likelihood that a message generates a level of engagement higher than the median level on Twitter and Facebook but increases that likelihood for messages from firms with a high-posting frequency on LinkedIn. Certain stakeholders may find messages irrelevant, inappropriate, or uninteresting on some platforms, except for Investor Relations content, which generated higher engagement on all three platforms.

While our results provide general insights on effectiveness of content strategies across SM platforms, we note that marketers should do closer systematical research about the effectiveness of SMMCS for their firm audiences. Identifying which content has the most favorable effect on engagement can be accomplished by performing A/B tests to explore alternative SMMCS effectiveness across contexts. Web Appendix A provides examples of messages that could inspire SM managers in their publications. Finally, our findings clearly highlight that the number of SM posts is a major driver of SMEB, both directly and indirectly, highlighting that without a programmatic approach to social media publishing, which involves systematically planning, executing, and optimizing the content published across SMPs, it will be difficult to attain engagement.

### 5.3. Study limitations and implications for future research

Like many studies, our research presents certain limitations while offering opportunities for future research. First, while this study builds on a large dataset compared to many other B2B studies, with 1700 messages from the 18 largest B2B firms in Canada across multiple industries, we call for new studies to confirm the generalizability of our findings with international datasets. We note that fast-developing web scraping tools and APIs (Boegershausen et al., 2022), along with machine learning and natural language processing tools for text categorization (Saravani et al., 2023), offer notable potential for large-scale research on social media engagement. Additionally, as the SM ecosystem continues to evolve, researching other platforms is warranted, as B2B companies are increasingly venturing into Snapchat, YouTube, Instagram, Bluesky, and TikTok, to name a few.

Second, this study measured social media engagement (SMEB) based on the aggregate level of standard behavioral reactions—such as love, like, haha, wow, celebrate, insightful, or curious—relative to platform mean values. Thus, our SMEB measure did not take into account broader engagement behaviors such as shares and comments nor the valence of the reactions. While we are confident that the SMEB measures used in this study provide a good approximation of the overall engagement level of a post, we note that future research should confirm our results with alternative, broader SMEB measures that include a message's comments and shares. Further, our data analyses focused on understanding above-average engagement on selected platforms, as we aimed to gain insight into the most engaging messages for these platforms. Future research could also use alternative continuous SMEB measures for more detailed results.

Third, our study only considered a partial and indirect "firm" effect (mainly, through the two control variable Messages and Followers) and in a non-explicit manner. Finally, even though our research is one of the few studies that consider firm messages across numerous social media platforms, we examined the global effect of messages on each platform independently and therefore we did not consider whether the messages were repeated across multiple platforms. An intriguing avenue for future research is the exploration of multi-platform messaging by comparing the SMEB for the same message across different platforms. Overall, future research can benefit from developing more rigorous approaches to enable comparisons and predictions of SMEB across multiple social media platforms. Many of those limitations should be taken into account in future research, which would clearly require a larger sample size and more advanced approach.

## CRediT authorship contribution statement

**Benoit Bourguignon:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Harri Terho:** Writing – review & editing, Writing – original draft, Visualization, Investigation, Conceptualization. **Ahlem Hajjem:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis.

## Appendix A. First-order SMMCS coding – definitions and illustrative message examples.

| Illustrative exemplary post | Definition of the SMMCS component | 1st order SMMCS component |
|---|---|---|
| "Monday is #OrangeShirtDay – an annual recognition of the Residential School system and its legacy – so remember to wear orange, as an act of remembrance and reconciliation. | Sharing information about community events | Community engagement participation |
| Volunteers at DAV Bill Nichols Chapter 13 Alexander City Al ensure no veteran is left behind by providing a variety of programs – including helping file casework, benefit claims & getting to & from appointments. Our donation of $10,000 is going to the purchase of a new van, which will be accessible to those who use wheelchairs or walkers. http://enb.fyi/ErUN50w4FBX | Giving money or voluntary work to the community | Community engagement strategy |
| Reducing greenhouse gas emissions is a key aspect to our business. Our Executive Vice Chairman Steve Laut spoke at the Natural Resources Summit hosted by @CalgaryChamber regarding the importance of GHG reduction #innovation in our industry #OurNaturalResources #technology #energy | Promoting the environmental reputation of the firm | Corporate environmental reputation |
| Ghislain Houle, CN's Executive Vice President and Chief Financial Officer, will be speaking at the CIBC 18th Annual Eastern Institutional Investor Conference on Wednesday, September 25, 2019 at 9:10 AM EDT. To listen to the webcast, click here: https://bddy.me/34S1piS | Publicizing a public declaration from the CEO or an upcoming speech | CEO public appearance |
| Bombardier announced today its clear roadmap to full year revenues, earnings and free cash flow guidance supported by planned fourth quarter delivery schedules at Aviation and Transportation. Read more: http://bit.ly/34f5qwC | Disclosing financial information or any news that could have an impact on the financial results like settling an issue with a community | Investment or divestment or any other financial news |
| It's hashtag#RailSafetyWeek! CN encourages communities all across its network in a joint safety effort [the company tries to reduce the number of casualties when people are crossing railroads]. Read more: https://bddy.me/2m6WXLi hashtag#RailSafety | General CTA not related to sales or recruitment or product | General Public Call to action (CTA) |
| Barbara from Jackson, MI, was thrilled to win a new kayak in our raffle at the Calhoun County fair. Congrats & happy paddling. | Invitation to play, to answer questions or revealing the results of a playful survey, of a contest for the public or even of an industrial competition | Non-commercial games and contests |
| We're pleased to share our list of Top Fans on Facebook right now! Magna values these users so much as they consistently share, comment and engage with our posts - helping spread the word about Magna! We can't thank you enough for supporting our team. #MagnaSpirit #MagnaStrong | Recognizing companies or people for achievements other than community service | Recognition of outsiders |
| Happy Hispanic Heritage Month! We are grateful for the contributions of the Hispanic community to our social and cultural fabric. | Wishes and greetings for an anniversary, a national holiday and the likes. It usually includes the word "happy…(holiday)" | Wishes and greetings |
| CN was proud to support the Richmond Chamber of Commerce's "Metro Vancouver on the Move" featuring Vancouver Fraser Port Authority, YVR, and TransLink on October 22. Thanks to Lucent Quay Consulting Inc.'s Pam Ryan for moderating. | Promoting an internal or an external event that does not have a direct commercial goal | Promoting non-commercial public relations (PR) events |
| CN is proud to be the main sponsor of the Indigenous Clean Energy Conference in Ottawa this week. Daniel Gagné, CN Manager of Aboriginal Relations, was present to engage with participants! | Promoting a tradeshow or a conference where the company will be present | Promoting commercial PR events |
| Every day we move 500 million passengers in 60 countries with safe, reliable, and ecofriendly mobility solutions. In honor of #WorldTourismDay, we're sharing our favorite cities from around the world that you can explore with Bombardier Transportation! #aroundtheworld Read more: https://www.bombardier.com/…/6-of-the-most-exciting-cities-… | Highlighting capabilities of the company in terms of manufacturing excellence, service, innovation etc… It is usually expressed in terms of performance or "how we…" or "that enable" or "we are the largest…" It can also promote its executive team. | Firm reputation |
| ICYMI: CN's Autonomous Track Inspection Program is a fully autonomous rail car that employs wireless communications to test and monitor real-time geometric track parameters without interrupting normal railroad operations [the company owns the railroad tracks and the program is part of a maintenance operation]. Powered by solar panels and a generator and travelling at revenue service track speed, our Autonomous Track Inspection Program uses the latest sensor and AI technology to deploy fully autonomous track inspections 24/7/365. Learn more here: https://bddy.me/2VW0REv #TechThursday | Announcing any news about a plant or a facility that includes information about the history of the firm | Facility or physical assets |
| Construction of Klang Valley mass rapid transit line 1 started in 2011. It included 51 km of alignment and 31 stations, with 9.5 km of track beneath the centre of | Presenting a factual description of product or project | Technical information about products and projects |

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(*continued*)

| Illustrative exemplary post | Definition of the SMMCS component | 1st order SMMCS component |
|---|---|---|
| Kuala Lumpur. SNC-Lavalin was involved as the independent consultant engineer. https://bit.ly/2kkQ3Bo | | |
| A launch ceremony was held at Magna's joint venture plant with HASCO in Shanghai to celebrate the production of our first electric drive unit in China. This is an exciting step forward in our electrified powertrain growth strategy and we look forward to many more milestones and successes. #MagnaGrowth #FutureTech | Publicizing the project or the new product advancement | Product and project development |
| The first export loads arrived this week at the @IntermobilCA terminal in Regina, SK. Learn more: https://bddy.me/32ijLYN #ReachFarther | Presenting how a product is been used or will be used | Demonstrating a product in use |
| This morning, Enbridge environmental inspectors conducting a routine storm water inspection on the Bad River Reservation reported detecting a faint odor. Crews were dispatched immediately to inspect the area, and as a precautionary measure Line 5 was shut down. The Bad River Band of Lake Superior Chippewa Tribe was notified.Response crews were on scene within an hour, detected no odor, and found no sign of a release. As an additional precaution, crews remained onsite as the line was restarted.Today was a confirmation that our safety process and protocols are working. Safety is our number one priority at Enbridge. | Showing how safe the project or the product is or what measures the company takes to ensure the safety of the users or the population | Communicating product or project safety |
| Nicolas Mabboux, Director Software Engineering Technology, tackled the topic of digitization as a competitive edge with attendees at the Association of Canadian Port Authorities "Anchored in Development" conference on September 11. Nicolas discussed how deploying advanced technologies is the next strategic driver of value for the supply chain and how data serves as a key asset, positioning IT as a digitization and business enabler. Hashtag#TechThursday hashtag#acpa2019 | Showing how a project or a product adds value and using words like "helping" (customers or products), "low-cost" "reliable" | Communicating product or project value |
| We love to celebrate great achievement from our team! Two of our designed projects were under the spotlight at the Malaysia Landscape Architecture Awards. Learn more here: http://bit.ly/2lOm2dw | Communicating many forms of referrals such as winning an award, employee "selling" the product or the service, or member of the community showing support | Product or project referrals |
| Organizations considering a hashtag#lean hashtag#agile transformation at scale need to be prepared to rethink their hashtag#outsourcing strategy. While each situation will be different, our new blog by Phil Van Sickel offers three key considerations to help increase outsourcing effectiveness in a lean agile environment. http://bit.ly/2jYxTFz | Calling for cognitive responses with online content, such as an invitation to consume company content, without a further contact with company | CTA for a cognitive involvement |
| Join us on Wednesday for our live webinar on delivering a citizen-centered collections solution on the Salesforce platform. It's not too late to register! http://bit.ly/2LyO0ogOur commitment to the safe and efficient movement of temperature-controlled goods goes hand-inhand with our commitment to constant innovation. Our remote monitoring AI technology is key to food safety. Come meet the CN hashtag#CargoCool team Produce Marketing Association hashtag#FreshSummit! Stop by booth 2602 to learn more about how we move fresh goods! hashtag#ReachFarther | Calling for a direct behavioral response with the firm, such as registering to an event or booking a meeting with company representatives | CTA for a behavioral involvement |
| We're attending the @nbmbaahq 2019 National Convention & Career Fair in #Houston – meeting prospective talent & chatting about exciting career opportunities. #NBMBAA | Promoting a career fair | Career fair |
| We're searching for ambitious, high-energy individuals with a passion for #innovation. Apply to join the team at our new Technology + Innovation Lab in Calgary or Houston: http://enb.fyi/rvUw50uBMWm. | Direct recruitment CTA or job posting | Recruitment |
| Suncor is proud to be playing a part in building the next generation of professional software testers in Indigenous communities. Check out the launch of a PLATO software tester internship training program - a new development in our successful partnership: http://sunr.gy/HKu050w3lal | Announcing internship opportunities | Internship |
| "Are you bilingual with strong customer-facing experience, and do you have experience handling customer issues/escalations?" | Using a question to describe an open position | Open position description with a question |
| "I never want a job that doesn't have a new challenge for me every day". Find out about Mike Samilski's exciting career journey to date: http://bit.ly/2m7boip #BeyondEngineering | Featuring an employee that shares their experience working for the company | Employee advocacy |
| "At Celestica you can inspire your curiosity and challenge yourself with complexity." | Promoting the benefits of working for the company to potential employees | Selling the employer brand |
| "We are taking steps to be a leader in inclusion and diversity. And, we are clearly focused on gender priorities, providing opportunities for women."—CEO Barry Perry to @Empire_Club | Promoting EDI or featuring an employee who is a member of a minority group | Promoting equity, diversity, and inclusion (EDI) |
| Happy Labour Day to our customers, employees and their families. Be safe today and every day. #LabourDay2019 Our powertrain team in Rosenberg, Germany, celebrated 2000 days without accidents! We thank you for keeping safety in mind and congratulations to all employees who have made this possible. #DrivingExcellence #MagnaPeople | Demonstrating how the firm takes care of employees or promoting a safe working environment for its employees | Caring |
| Lisa Ross, Supplier Diversity Manager at Magna, was recognized for being the "Corporate Advocate of the Year" by the @GreatLakesWBC. Congratulations! Read Lisa's story: http://bit.ly/2N6rNxa #WomenatMagna | Praising individuals or a group for an achievement. The text often uses "thank you" or "congratulations" or "we are proud of this employee" | Praise |
| "It's hashtag#CybersecurityAwarenessMonth and CN is helping employees remain proactive about managing online threats and continuously improve data protection." | Presenting job application tips, publicizing employee training activities or internship opportunities | Training and development |

## Appendix B. The full cartesian grid search of the tunning approach of RF models hyperparameters.

**Table B1**
Hyperparameters values considered in the grid search

| Hyperparameter | Values |
|---|---|
| Number of trees (*num.trees*) | The 30 numbers of the sequence starting at 100 and ending at 3000, with 100 as increment |
| Number of variables to possibly split at each node (*mtry*) | 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13 |
| Minimal node size to split at (min.*node.size*) | 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 15, 20 |
| Sample with replacement (*replace*)? | TRUE, FALSE |

Notes. 1) Overall, 8640 hyperparameter combinations were considered. Therefore, for each platform, 8640 RF models were fitted using the corresponding training data and the R function ranger (Wright & Ziegler, 2017) with each one of the grid's combinations. Each time, the out-of-bag (OOB) prediction error is saved. The grid search took 40, 34, and 34 min in the Twitter, Facebook, and LinkedIn cases, respectively. 2) In RF models, the data points that are not included in the bootstrap sample for a particular tree are called out-of-bag (OOB) samples. These samples are excluded from the training of that specific tree. Each tree in the forest can make predictions for the OOB samples that were not used in its training. By aggregating the predictions for each OOB sample across all the trees where it was not included, an overall prediction for each data point can be made. The OOB error is calculated by comparing the aggregated OOB predictions with the actual values of these samples. This error rate provides an unbiased estimate of the model's generalization error because the OOB samples were not used in training the corresponding trees.

**Table B2**
Best hyperparameters combinations

| SMP | num.trees | mtry | min.node.size | replace | OOB.MCE |
|---|---|---|---|---|---|
| Twitter | 1500 | 4 | 20 | FALSE | 0.32 |
| Facebook | 500 | 2 | 20 | TRUE | 0.22 |
| LinkedIn | 100 | 12 | 10 | TRUE | 0.23 |

Note. The best hyperparameters combination is the one that results in the smallest out-of-bag misclassification error (OOB.MCE).

## Appendix C. Performance results of final RF models.

| SMP | Recall | Precision | F1 | Accuracy | AUC |
|---|---|---|---|---|---|
| Twitter | 0.67 | 0.66 | 0.67 | 0.68 | 0.74 |
| Facebook | 0.76 | 0.65 | 0.70 | 0.68 | 0.81 |
| LinkedIn | 0.67 | 0.75 | 0.71 | 0.73 | 0.81 |

Notes. 1) There are 166 (47.98 %) high SMEB posts in Twitter test data, 123 (49.40 %) in Facebook test data, and 126 (49.61 %) in LinkedIn test data. 2) These results are derived using the R package DALEX (Biecek, 2018) and its two functions, explain and model performance. 3) The F1 score is a single metric that combines precision and recall and ranges between 1, i.e., perfect precision and recall, and 0 when neither is achieved at all. 4) The area under the Receiver Operating Characteristic (ROC) curve (AUC-ROC) is a performance measurement for classification problems that shows how well a model distinguishes between classes across all thresholds, 5) Twitter, Facebook and LinkedIn RF models have good predictive performance as they achieved an accuracy exceeding the 50 % threshold by more than 25 % (Hair et al., 2019, p. 502); their F1 scores imply that they made fairly accurate predictions, i.e., they classified high-engagement messages correctly while capturing a good number of actual high-engagement messages, and their ROC-AUC values are much higher than the random model 50 % ROC-AUC metric.

## Appendix D. Descriptive statistics of Followers, Messages, Message length, and Number of reactions, before their binarization.

| Twitter | | | | |
|---|---|---|---|---|
| Statistic \ Variable | *Followers* | *Messages* | *Message length* | *Number of reactions* |
| *Mean* | 20,761.2 | 81.1 | 200.1 | 9.2 |
| ***Median*** | **15,800.0** | **62.0** | **202.0** | **7.0** |
| *Standard Deviation* | 22,515.4 | 55.2 | 65.6 | 9.3 |
| *Minimum* | 1982.0 | 9.0 | 42.0 | 0.0 |
| *Maximum* | 137,600.0 | 172.0 | 407.0 | 120.0 |
| *Interquartile Range* | 14,328.0 | 33.0 | 99.0 | 8.0 |
| *Skewness* | 3.8 | 0.8 | −0.1 | 4.5 |
| *Kurtosis* | 17.3 | −0.8 | −0.1 | 37.9 |

| Facebook | | | | |
|---|---|---|---|---|
| Statistic \ Variable | *Followers* | *Messages* | *Message length* | *Number of reactions* |
| *Mean* | 59,140.2 | 55.9 | 295.4 | 201.4 |
| ***Median*** | **62,051.0** | **49.0** | **267.0** | **42.0** |
| *Standard Deviation* | 42,610.3 | 32.7 | 169.1 | 880.7 |
| *Minimum* | 2308.0 | 3.0 | 31.0 | 0.0 |
| *Maximum* | 180,269.0 | 112.0 | 2056.0 | 9257.0 |
| *Interquartile Range* | 75,132.0 | 23.0 | 154.3 | 73.0 |

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(*continued*)

| Facebook | | | | |
|---|---|---|---|---|
| Statistic \ Variable | *Followers* | *Messages* | *Message length* | *Number of reactions* |
| *Skewness* | 0.4 | 0.8 | 4.3 | 7.5 |
| *Kurtosis* | −0.5 | −0.6 | 34.4 | 60.8 |

| LinkedIn | | | | |
|---|---|---|---|---|
| Statistic \ Variable | *Followers* | *Messages* | *Message length* | *Number of reactions* |
| *Mean* | 244,538.2 | 52.3 | 314.8 | 175.9 |
| ***Median*** | **267,730.0** | **56.0** | **278.0** | **112.0** |
| *Standard Deviation* | 162,952.1 | 24.9 | 188.4 | 196.1 |
| *Minimum* | 2678.0 | 1.0 | 22.0 | 0.0 |
| *Maximum* | 527,202.0 | 85.0 | 1300.0 | 1683.0 |
| *Interquartile Range* | 301,944.0 | 47.0 | 137.3 | 161.3 |
| *Skewness* | 0.3 | −0.3 | 2.8 | 3.2 |
| *Kurtosis* | −1.2 | −1.1 | 11.1 | 15.0 |

## Appendix E. Control variables distribution across Twitter, Facebook, and LinkedIn.

| Control variables | | TW | FB | LI | Total | χ2 | P | Sig. |
|---|---|---|---|---|---|---|---|---|
| Origin: *Shared* | % | 9 % | 14 % | 1 % | 8 % | 55.86 | 0.000 | ** |
| | *n* | 64 | 71 | 7 | 142 | | | |
| Media richness: *Video & text* | % | 8 % | 14 % | 13 % | 11 % | 114.99 | 0.000 | ** |
| | *n* | 52 | 70 | 64 | 186 | | | |
| Media richness: *Image & text* | % | 70 % | 66 % | 85 % | 74 % | | | |
| | *n* | 485 | 330 | 436 | 1251 | | | |
| Media richness: *Text only* | % | 22 % | 20 % | 2 % | 15 % | | | |
| | *n* | 155 | 98 | 10 | 263 | | | |
| Followers: *High* | % | 44 % | 43 % | 56 % | 47 % | 23.27 | 0.000 | ** |
| | *n* | 302 | 216 | 287 | 805 | | | |
| Messages: *High* | % | 46 % | 44 % | 43 % | 45 % | 1.04 | 0.596 | n.s. |
| | *n* | 319 | 219 | 221 | 759 | | | |
| Message length: *High* | % | 51 % | 50 % | 49 % | 50 % | 0.24 | 0.887 | n.s. |
| | *n* | 350 | 247 | 251 | 848 | | | |
| *Total* | | 692 | 498 | 510 | 1700 | | | |

Note. ** p<. 01; * p<. 05; +p<. 10, n.s. not significant.
TW: Twitter, FB: Facebook, LI: LinkedIn, χ2: Chi-square.

## Data availability

Data will be made available on request.

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