The outcome of online social interactions on Facebook pages
A study of user engagement behavior

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Abstract
Purpose – The purpose of this paper is to investigate the impact of different ways of message framing on users’ engagement behavior regarding the brand posts on Facebook and to determine whether users’ thumbs-up and reply moderate this impact.
Design/methodology/approach – A panel data analysis was conducted on a panel with 11,894 observations on 850 unique brand posts from the Facebook pages of the world’s most valuable brands over a seven days window with two observations each day. A system of equations was estimated using ordinary least squares, Hausman–Taylor IV and seemingly unrelated regressions to test study’s hypotheses.
Findings – The empirical findings confirm that more positively and negatively framed comments result in increased users’ engagement. Also, an increase in thumbs-up ratio for neutrally and negatively framed comments results in less engagement. The reply ratio might also have a positive and negative moderation effect on the influence of neutrally and positively framed comments on engagement behavior, respectively.
Practical implications – This study provides an in-depth understanding of online social interactions on Facebook pages for firms’ managers and marketers. Online social interactions might be either harmful or fruitful for firms depending on the type of interaction and engagement behavior. Findings can help managers and marketer to improve their strategies for leveraging Facebook for electronic marketing.
Originality/value – This is likely to be the first study that examines the moderating effect of users’ thumbs-up and reply on the relationship between message framing and users’ engagement behavior. By providing robust findings by addressing issues like omitted variables and endogeneity, the findings of this study are promising for developing new hypotheses and theoretical models in the context of online social interactions.
Keywords Facebook, User engagement, Social media marketing, Online brand community, Electronic word-of-mouth, Online social interactions
Paper type Research paper

1. Introduction
Social media is an inevitable part of people’s daily life. Social media propounded another way of interaction between people, and also a new form of interaction between people (or particularly customers) and firms. Over the recent years, many firms started using social media as a means of interaction with their customers. Interestingly, in some social media platforms like Facebook, there is an opportunity for companies to establish their online community. A social media brand community (SMBC) is a specific type of online brand communities that helps firms to achieve better customer loyalty and a better relationship with customers (Habibi et al., 2014; Laroche et al., 2013). Meanwhile, understanding consumers’ participation in the SMBC-related activities is essential for firms as customers can easily share their thoughts and experiences about the firm with other customers (Heinonen, 2011). Participation in activities related to SMBCs opens doors into social

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interactions between customers or users in general. The most popular kind of online social interaction is word-of-mouth (WOM) communication that has been underlined in the literature as it can be either fruitful or harmful for the firms (see e.g. Goes et al., 2014; Luo and Zhang, 2013; Ray et al., 2014). However, there are other kinds of social interactions on SMBCs that need to be investigated to understand the antecedents and consequences of such social interactions better.

Using social media as a marketing channel can be influential for firms in different ways. Social media can be useful for companies to improve their long-term financial performance (Rishika et al., 2013); estimating their online reputation (Manaman et al., 2016); developing innovations (Dong and Wu, 2015); or generating sales (Goh et al., 2013). However, some argue that social media may bring about negative consequences for firms as customers can speak out their thoughts and easily interact with each other while companies cannot control the flow of such information in this environment (Laroche et al., 2013). While social media research mostly concentrates around the notion of beneficial consequences of online interactions between customers on social media, there are possibly unsought and unfavorable consequences of such interactions for brands that need to be studied (Adjei et al., 2016). Therefore, it is essential to focus on the unsought consequences of social interactions on social media for firms.

In SMBCs, any user of social media (followers and non-followers of the brand community) can interact with brands’ posts as these pages, and their posts are public. Therefore, those who interact with brands’ posts are not only brands’ customers but also any random user of social media. They might be brands’ advocates or adversaries. In Facebook, when a user engages with a post (e.g. leaving a comment on the post), that post will possibly appear on her friends’ News Feed (Hsu et al., 2015; Kumar et al., 2017). As a result, they may either choose to interact with or view the post without any meaningful interaction. A similar information dissemination mechanism also exists on other social media platforms such as Instagram and Twitter. When a post gets disseminated to a very large extent on social media platforms a social epidemic happens, which is beneficial for companies to promote their brands (Shi et al., 2018). With new changes in Facebook’s News Feed algorithm at the beginning of 2018, a brand post will have a higher chance to appear on a user’s News Feed if her friends or family already interacted with that post (Bromwich and Haag, 2018; Hsiao, 2018; Vogelstein, 2018). In this regard, brand page managers are advised to focus on the ways they can increase meaningful engagement of users to have a higher exposure – named as Facebook “impressions” – among Facebook users. Facebook impressions are a good indicator of the effectiveness of SMBC and acquiring a higher impression can increase average weekly sales of a brand (Kumar et al., 2017).

The administrators of Facebook pages have no control over the order of comments on their posts that are visible to the public. They can hide or delete comments from a post (Facebook, 2017). However, users can identify if they would like to see comments in chronological order or “top comments” first. The way comments are sorted in a post on Facebook by default, namely, “top comments” follows a specific algorithm that considers different elements. One of the important and effective elements is the number of times other users gave a “thumbs-up” (i.e. like button in the comment section) to a comment. Giving a thumbs-up to users’ comments is a common practice in many social media platforms, while each platform may use a different name for this function (e.g. “up-vote”). Comments with more up-votes will be more prominent as they are shown on top of the comment section (Priestley and Mesoudi, 2015; Noguti et al., 2016). In this regard, it is likely that a negative comment with a high number of thumbs-up sits on top of the comments section with the highest chance of exposure to users. Further, when we react to a user’s comment by giving it a thumbs-up, it may change others’ perception of the reliability of the comment. Therefore, it is important to understand whether giving a thumbs-up to comments moderates the plausible influence of those comments on users’ engagement behavior.
Another way of online social interaction on Facebook pages and many other social media platforms (e.g., Youtube and Instagram) is leaving a reply to others’ comments. Leaving a reply is analogous to direct interaction with a customer or marketer and prior research has shown both directed customer-to-customer (C2C) or marketer-to-customer interactions can positively influence the purchase behavior of customers (Goh et al., 2013). Besides, channel characteristics like sensory modes (e.g., reply count in Facebook pages) are likely to moderate the effects of WOM and C2C interactions on purchase behaviors (Libai et al., 2010). So, it is plausible that leaving a reply to a user’s comment by either other users or marketers (i.e., brand page administrators) changes users’ perceptions and intentions. Thus, it is also important to understand whether leaving a reply to comments is likely to moderate the plausible influence of those comments on users’ engagement behavior.

Following to Lee and van Dolen (2015), this study draws on the signaling theory and message framing to investigate the plausible association between collective sentiments (i.e., the aggregated individual user sentiments embedded in their comments) and the level of users’ engagement with brand posts on Facebook pages. Simply put, this study examines the impact of message framing on engagement behavior of users in brands’ Facebook pages. Also, we further study whether users’ “thumbs-up” and “reply” on comments moderate the impact of message framing on engagement behavior of users. As a preliminary investigation on the notion of thumbs-up and reply in online social interactions on Facebook pages, this empirical study enlightens interesting insights both for theory and practice. The empirical findings confirm that more positively and negatively framed comments result in increased users’ engagement. Also, an increase in thumbs-up ratio for neutrally and negatively framed comments results in less engagement. The reply ratio might also have a positive and negative moderation effect on the influence of neutrally and positively framed comments on engagement behavior, respectively.

This research provides important contributions to the literature. First, unlike the other studies in the context of SMBCs, this study explains the most important types of online social interactions and their influence on users’ engagement behavior on SMBCs using the theoretical lens of message framing and signaling theory. Second, this research extends the theoretical explanations on the way message framing influences the human behavior by adding the moderation effect of “thumbs-up” that is an indicator of endorsement or agreement with a message, and “reply” that is a good signal of conversation dynamics. This study sheds light on an essential aspect of online social interactions on Facebook pages, which is useful for practitioners and managers. Also, findings are promising for future studies and suggestions are provided for future research, which can lead to the development of new hypotheses and theoretical models about online social interactions in social media.

2. Literature review

The virtual or online brand communities have been studied by scholars and practitioners of information systems and marketing over the past decade. SMBCs, however, are a more recent focused area of research. Although an SMBC is a sort of virtual brand community, there are several important differences between them (see Habibi et al., 2014). Thus, we exclusively focus on SMBCs in this study. Online social interactions on SMBCs can be among firms and users (through either firm-generated content (FGC) or UGC) or between users (through UGC). We can classify the research in the context of SMBCs and online social interactions into two major directions. First, studies that focused on the way online social interactions on SMBCs might influence business performance. Second, studies that focused on the idea that online social interactions on SMBCs might affect participation in SMBCs and community-related activities. The latter is the focus of this research; however, a review of studies related to both directions is presented in the following.
2.1 SMBCs and business performance
Various studies have illustrated the advantages that online social interactions on SMBCs can provide for firms regarding business performance. Wang et al. (2015) investigated the impact of FGC and UGC of Facebook fan pages on offline purchase behavior of consumers in the US automobile industry. Scholz et al. (2013) investigated the impact of FGC and UGC on consumers' awareness, interest and purchase decision. Similarly, Xie and Lee (2015) referred to UGC and FGC in SMBCs as earned and owned social media activities, respectively, and then examined the impact of these activities on purchase decision making of consumers. Kumar et al. (2017) suggested that synergetic effect of both traditional marketing and social media marketing via brand's Facebook page can reduce a brand's marketing cost around $0.4m per annum. In such synergetic effect, the overall exposure of the brand to Facebook users (i.e. Facebook impressions) can influence brand sales.

Goh et al. (2013) extracted information and persuasion features of UGC and FGC using a text mining tool that employs a lexicon for sentiment analysis. They examined how those features influence purchase behavior of consumers by considering directed and undirected communications between marketers and consumers. Finally, they showed that UGC has a stronger influence on consumer purchase behavior rather than FGC. Similarly, Tang et al. (2014) applied an analogous sentiment analysis approach on UGC retrieved from Facebook and YouTube and focused explicitly on neutral UGC and examined its impact on product sales. Wu et al. (2015) analyzed consumers' emotional biases in an online brand community by utilizing sentiment analysis to classify them into two distinguished groups; then, they examined the influence of level of activity of each group in the brand community on their purchase frequency.

2.2 SMBCs and user engagement behavior
In general, consumer social participation in SMBCs is a broad and multidimensional construct (see Kamboj and Sarmah, 2018). However, prior research has investigated and measured consumer social participation in SMBCs in a more specific way. Some studies investigated participation in SMBCs (or in other words becoming a fan or follower of the SMBCs) as a desiring outcome for firms. As an example, Ding et al. (2014) investigated the plausible impact of FGC and UGC on the growth of SMBCs (i.e. the rate of increase of community members). On the other hand, there is research that focused on participation in community-related activities (or explicitly engaging with brand posts) as the desiring outcome for firms. In this regard, there are three kinds of engagement behavior that have been studied in the context of SMBCs including liking a post, commenting on the post and sharing the post, which are addressed in our research. Each one of these activities portraits different level of engagement (Kim and Yang, 2017). Accordingly, liking has the lowest level of engagement as just one click is needed. While commenting and sharing need more cognitive effort and commitment than liking and yet the sharing pertains a higher level of engagement.

De Vries et al. (2012) focused on identifying the factors that can affect likes' count and comments' count of a post in SMBCs. They provided useful insights by analyzing brand-related posts from various international brands; for instance, if a post contains positive comments more than negative ones, there would be a positive impact on post likes' count. Sabate et al. (2014) analyzed posts from several different travel agencies and they showed content richness is an important influencing factor to gain more likes' count for a post. On the one hand, putting website links in the content of a post may have a negative impact on comments' count. On the other hand, providing images in the content of a post and a choosing an appropriate time to publish the post on the brand community would have a significant effect on comments' count. Engagement behaviors such as liking and commenting have been investigated in prior research in the context of SMBCs (e.g. De Vries et al., 2012; Relling et al., 2016) more than sharing.
There are also studies that investigated the antecedents of consumer engagement in SMBCs in a more general and conceptual way. For instance, Islam et al. (2018) used the theoretical lens of congruity theory to show how value congruity and self-brand image congruity can affect consumer engagement by surveying 443 members of SMBCs.

Another way of online social interaction in some of the social media platforms (e.g. Facebook and Reddit) is the act of liking or up-voting a user’s comment, which is also another kind of community-related activity that users can do corresponding to anyone’s comment. There may be a handful of studies that investigated the up-voting behavior in an online environment to provide a better understanding of the antecedents that affect such behavior (Muchnik et al., 2013; Priestley and Mesoudi, 2015; Stephens et al., 2016). However, there is perhaps no study in the context of SMBCs that investigated this kind of reaction to users’ comments as an antecedent of users’ engagement with brand posts. Likewise, leaving a reply to users’ comments is another type of online social interaction that seems to be overlooked in the literature. Although a similar online social interaction has been addressed by Goh et al. (2013) as “direct customer-to-customer or marketer-to-customer interactions” and it is shown that such interaction can positively influence the purchase behavior of customers, the “reply” function in SMBCs and its role regarding user engagement behavior needs attention. Therefore, in this study, we focused on the plausible consequences of such online social interactions for brand posts.

3. Theoretical foundation and hypotheses

Based on information asymmetry, two different parties (sellers and buyers) can access to varying levels of information. Information asymmetry is evident in the current status of online marketing (Tsao et al., 2011). For instance, information asymmetry happens when the seller provides minimal information about products on an online shopping website. In e-business, buyers usually confront information asymmetry because it is not possible to physically evaluate product quality or easily judge the trustworthiness of seller (Mavlanova et al., 2012). In such circumstances, website signals are an excellent source of information to help consumers judge the quality of product or seller. Tsao et al. (2011) refer to signals as pieces of information that customers can use when there is no access to perfect information about the quality of offerings.

This mechanism exists in online communities as well, and research has adapted the theoretical lens of signaling to explain users’ participation in online communities. In an online community, there is usually the problem of information uncertainty about the content that either administrators or users generate and it may affect users’ participation in the activities of the online community. To mitigate this problem, information technology features (e.g. ratings, reviews) for contents can serve as a signal of quality and reliability for the content (Benlian and Hess, 2011). Also, social information cues (e.g. peer consumer purchase or peer consumer review) on online social communities serve as signals that can lead consumers to make purchase decisions (Cheung et al., 2014). Signaling theory posits that peripheral cues are a source of information that individuals tend to rely on them when they are making a decision (Lee and van Dolen, 2015). Accordingly, we argue that when users consume content of an SMBC, they also rely on the existing signals beside the content itself to decide whether they want to engage with the post or not. Drawing on signaling theory and message framing, Lee and van Dolen (2015) argued and suggested that collective sentiments that are derived from either positively or negatively charged words embedded in texts are analogous to peripheral cues that influence individuals’ decision making. According to their study, collective sentiments influence a user’s activities in an online co-creation community and consequently the performance of the online community.

Users tend to engage in post-related activities and consume contents such as reading post-related comments written by other users. Some users tend to read or seek information in other users’ comments. We argue that users’ participation in post-related activities might be influenced by the exposure to different sentiments embedded in users’ comments. The reason
is that one of the influential factors for a human's evaluations and decision-making process is the way they frame information. According to the message framing theory, when a message is affectively loaded (whether it is positively or negatively framed), it will evoke extensive cognitive processing in the receivers such as paying more attention (Smith and Petty, 1996). This extensive cognitive processing leads to behavioral responses from the receiver. Prior research has argued how different message framing approaches affect consumers' behaviors such as purchase and buying behavior (e.g. Christodoulides et al., 2012) or participatory behaviors (e.g. Lee and van Dolen, 2015; Stieglitz and Dang-Xuan, 2013). In an SMBC context, the way users frame their opinion regarding a post matters as if they use more affectively charged terms in framing their comment this signal might draw attention among those who see the comment. Especially, sharing opinions in written communication might be more constructive since there is naturally more time to think and frame messages (Berger and Iyengar, 2013). Since the sentiment embedded in comments as a whole creates an affective environment by users who left the comments, the collective sentiments can be considered as antecedents of the future behavior of users (Lee and van Dolen, 2015).

De Vries et al. (2012) showed that leaving positive comments on brand posts is positively related to the number of times users either like brand posts or leave a comment on them and sharing negative comments might lead to leaving more comments on brand posts in SMBCs. Positive feeling or emotion is also found to be a trigger for individuals to have an urge for sharing information on microblogs instantly (Wang et al., 2017). It is shown that both positive and negative WOM can evoke more consumer engagement in SMBCs depending on the type of community (Relling et al., 2016). Perhaps the difference between engagement stimulated by positively and negatively framed signals is that they lead to positive engagement and negative engagement (e.g. leaving a negative comment), respectively. However, negatively framed signals grab more attention, and they receive higher scrutiny comparing to positively framed signals (Smith and Petty, 1996; Lee and van Dolen, 2015). Accordingly, we expect both positively, and negatively framed comments might be positively associated with the level of users' engagement with brand posts:

H1a. Positively framed comments increase users' engagement behavior.

H1b. Negatively framed comments increase users' engagement behavior.

The notion of neutral sentiments is barely investigated as a message framing approach and an antecedent of individuals' engagement with the online content. Regardless of the theoretical framework, only a handful of studies investigated the notion of neutrality in UGC and its plausible impact on purchase outcomes. Sonnier et al. (2011) showed a positive relationship between neutral comments and sales performance. Also, neutral UGC has a positive effect on the rate of those customers who are persuaded in a firm's Facebook page to visit and buy products from firm's online shop (Scholz et al., 2013). The notion of neutrality can be even more complex. Tang et al. (2014) examined the influence of neutral comments on product sales. They classified neutral comments into two groups of mixed-neutral (i.e. equivalent combination of positive and negative sentiments) and indifferent-neutral (i.e. purely neutral) and showed they have a positive and negative impact on product sales, respectively. However, current study considers these two groups as a single group of neutral comments. Accordingly, we expect a positive association between neutrally framed comments and the level of users' engagement with brand posts:

H1c. Neutrally framed comments increase users' engagement behavior.

In an online community, there is usually the problem of information uncertainty about the content that users generate and it may affect users' participation in the activities of the online community. Information technology features such as ratings for contents can serve as a signal of quality and reliability for the content and mitigate the problem of information
uncertainty (Benlian and Hess, 2011). In Facebook pages, not only can users engage with brand posts, but also other users’ comments. One of the ways to engage with a user’s comment is to click on the “like” button associated with the comment, or in other words, to give a thumbs-up to the comment. This feature is analogous to the up-voting or rating feature on other social media platforms such as Reddit. When more users give a thumbs-up to a comment, it might be perceived in different ways. For instance, when a comment gains many up-votes by other users, it shows that all those users might have the same opinion (Ngoc and Yoo, 2014) or they support the expressed opinion (Chen et al., 2011). Thus, it can serve as an endorsement for the content of the comment, and it may affect the perception of users about the reliability of the comments. By default, those comments with higher up-votes will be promoted and positioned, first, in the list of comments and will be more prominent (Priestley and Mesoudi, 2015; Noguti et al., 2016). On the contrary, comments with less or no up-votes will be positioned at the lower places in the list of comments and users need to scroll down to observe them. Majchrzak et al. (2013) referred to up-voting a comment as a sort of “metavoicing” and declared that metavoicing is likely to either foster or inhibit the productivity of the knowledge conversations in different circumstances. Similarly, up-voting may increase the informational exchange on a Q&A website (Rechavi and Rafaeli, 2012). However, users can be still skeptical about the credibility of such a signal and show different levels of participation in an online community (Benlian and Hess, 2011). Accordingly, we posit that users’ thumbs-up will moderate the impact of message framing on the level of users’ engagement. Thereby, we propose the following hypotheses:

**H2a.** Thumbs-up ratio moderates the influence of positively framed comments on the engagement behavior of users.

**H2b.** Thumbs-up ratio moderates the influence of negatively framed comments on the engagement behavior of users.

**H2c.** Thumbs-up ratio moderates the influence of neutrally framed comments on the engagement behavior of users.

Leaving a reply is different from leaving a comment on a post. As Goh et al. (2013) introduced two ways of interaction between customers and marketers; we can assume leaving a reply is analogous to direct interaction with a customer or marketer. Likewise, leaving a comment is more similar to undirected interactions on Facebook pages. Prior research has shown both directed C2C or marketer-to-customer interactions can positively influence the purchase behavior of customers (Goh et al., 2013). So, it is plausible that leaving a reply to a user’s comment by either other users or marketers (i.e. brand page administrators) changes users’ perceptions and intentions. Leaving a reply not only can be a reason for the replier to come back and leave another reply but also helps the conversation grow and be more interactive as it leads other users to join the conversation (Shoham et al., 2013). Libai et al. (2010) suggested that channel characteristics like sensory modes in branded environments (e.g. online brand communities) are likely to moderate the effects of WOM and C2C interactions on purchase behaviors and there should be research to test it. Follow up to this argument, we argue that one of the distinct sensory modes in a Facebook page is the reply count that is shown in the interface and it is a potential signaling mechanism. We postulate that if such signaling mechanism can potentially moderate the impact of WOM and C2C interactions on purchase behaviors, it has the potential to moderate the impact of WOM and C2C on other forms of human behavior. Thus, we posit the average reply count is likely to moderate the impact of message framing on the users’ engagement behavior. Thereby, we propose the following hypotheses:

**H3a.** Reply ratio moderates the influence of positively framed comments on the engagement behavior of users.
H3b. Reply ratio moderates the influence of negatively framed comments on the engagement behavior of users.

H3c. Reply ratio moderates the influence of neutrally framed comments on the engagement behavior of users.

4. Research methodology

4.1 Data description and measurements
We collected the data from the official Facebook pages of the most valuable brands in the Technology sector according to the Forbes (2018) ranking. We could find the official Facebook pages of 17 out of 18 brands from which we collected data. Because the population of brand posts on each brand page is indistinctive, using a probability sampling method can be challenging. In this regard, we used a convenience sampling method. Although convenience sampling may raise the concern on the sampling error, selection bias and generalizability of findings, it has applied to a variety of studies related to Facebook (e.g. Cheung and Lee, 2010; Khan and Jarvenpaa, 2010; Kim and Yang, 2017). This method can be useful for a preliminary study similar to this research. For data collection, we developed a program to connect to Facebook application programming interface (API) using R programming language. We created a program to retrieve the last 50 posts (before February 1, 2018) that were published on each brand page. By brand posts, we mean any content that is posted on the online brand community by its administrators but not regular individual users. Then, we observed each of these posts to track the engagement behavior of users over a week, twice a day every 12 h and retrieved their data to create a panel data of brand posts.

Like, comment and share frequency ($L_{\text{Freq}}$, $C_{\text{Freq}}$, $S_{\text{Freq}}$). As we mentioned before, there are three common ways to engage with a post on most of the social media platforms, and we considered these three as the main dependent variables of the analysis. Similar to prior studies, we considered the number of times that users liked the post, the number of comments related to the post and the number of times that users shared the post (De Vries et al., 2012; Kim and Yang, 2017). These numbers are the ones that are shown on each Facebook post at the time of data collection, which are the cumulative frequency of likes, comments and shares of each post on the time of observation in a unit of thousands. We considered a natural logarithm transformation of these variables due to the skewness of their distribution.

Positive, neutral and negative comments frequency ($\text{PosFreq}$, $\text{NeuFreq}$, $\text{NegFreq}$). Similar to data collection, we used R programming language to develop a program to deal with cleaning and processing of users’ comments. First, we cleaned any comment consisting of anything except text such as emoticons or hyperlinks. Also, we only considered comments with the English language for further analysis and withdraw all non-English comments. It should be mentioned that the objective of this study was not to propose a new sentiment analysis algorithm. So, our program utilized a lexicon-based sentiment analysis approach (Naive Bayes) along with the subjectivity lexicon from Wiebe and Mihalcea (2006) to label all comments regarding sentiment class. The program computes the probability of membership in each sentiment class (i.e. positive, negative and neutral) for each comment based on the commonality of terms in the comment and the lexicon. Then, it assigns the sentiment class with the superior likelihood to the comment. After identification of the sentiment class for all comments, the program calculated the frequency of each sentiment class (i.e. positive, neutral and negative) for every post and stored the results in the final panel. This measurement for different sentiment classes is similar to what has been used in prior research (see e.g. Tang et al., 2014).

Thumbs-up ratio ($\text{TRatio}_{\text{POS}}$, $\text{TRatio}_{\text{NEU}}$, $\text{TRatio}_{\text{NEG}}$). We determined the thumbs-up count for each class of comments per each post and then took the average of them. However, it is possible to face a situation where no comments in a specific class (e.g. neutral) receive any thumbs-up. So, the raw
The thumbs-up ratio is summed up with one to obviate this impediment (Ngoc and Yoo, 2014). The following equation shows the final measure of the thumbs-up ratio for positive comments of post \( i \) at day \( t \). Since the unit of analysis in our study is a Facebook post, \( i \) refers to the post number in all our equations. Also, the time unit in our panel data is a “half a day or a 12 hours period.” Thus, \( t \) refers to the observation time (i.e. a half-day or 12 h period) in all our equations:

\[
TRatio_{\text{POS}}(it) = \left( \sum_{k=1}^{K} TCount_{\text{POS}}(kit) / PosFreq_{it} \right) + 1, \tag{1}
\]

where \( k \) is the comment number \((k = 1, 2, \ldots, K)\); and \( TCount_{\text{POS}}(kit) \) the thumbs-up count for the \( k \)th positive comment of post \( i \) at time \( t \). Also, we used the same measure as Equation (2) for the thumbs-up ratio of negative comments (i.e. \( TRatio_{\text{NEG}}(it) \)) and neutral comments (i.e. \( TRatio_{\text{NEU}}(it) \)).

Reply ratio \((\text{RepRatio}_{\text{POS}}(it); \text{RepRatio}_{\text{NEU}}(it); \text{RepRatio}_{\text{NEG}}(it))\). Similar to thumbs-up ratio, we determined the reply count related to each class of comments per each post and then took the average of them. Then, it is summed up with one to obviate cases where no comments in a specific class (e.g. neutral) receives any reply and the average reply count for that class may become zero. The following equation shows the final measure of the reply ratio for positive comments:

\[
\text{RepRatio}_{\text{POS}}(it) = \left( \sum_{k=1}^{K} RepCount_{\text{POS}}(kit) / PosFreq_{it} \right) + 1, \tag{2}
\]

where \( k \) is the comment number \((k = 1, 2, \ldots, K)\); and \( RepCount_{\text{POS}}(kit) \) the reply count for the \( k \)th positive comment of post \( i \) at time \( t \) (i.e. “half a day or a 12 hours period”). Also, we used the same measure as Equation (2) for the reply ratio of negative comments (i.e. \( \text{RepRatio}_{\text{NEG}}(it) \)) and neutral comments (i.e. \( \text{RepRatio}_{\text{NEU}}(it) \)).

Post type \((\text{PostType}_i)\). This control variable is the type of content of each post that brands published on their Facebook page, which is one of the following four types: video, photo, link and status. These four categories are identified by Facebook as we received them in data collection.

Post age \((\text{PostAge}_{it})\). A newly published post has more chances to appear in users’ news feed in comparison to older posts. In other words, older posts may be less impactful than the new ones (Rishika et al., 2013). However, users should visit the brand Facebook page and scroll down to see old posts and engage with them. That is why the time interval between the creation time of a post and the time of data collection is important to notice. Therefore, this time difference was considered as an exogenous variable in the analysis and then controlled in the model as a time lag for brand posts. We considered a natural logarithm transformation of this variable due to the skewness of its distribution.

Page fans count \((\text{PageFans}_{it})\). Since each brand page has a different number of fans, a post from a brand page with 1m fans has the better likelihood to have higher impressions, and more users might engage with it compared to a post from a brand page with 100k fans. This page-level control variable is the number of fans of each brand page at each observation time in our model specifications. We considered a natural logarithm transformation of this variable due to the skewness of its distribution.

Brand \((\text{Brand}_i)\). This is the second page-level control variable in our model specifications to control for any other omitted and unobserved page or brand-specific heterogeneity. This variable is a categorical variable accounting for brand-specific heterogeneity regarding each post.

After we processed the retrieved data for constructing the abovementioned variables and our panel data, we utilized the final panel data to examine the proposed hypotheses. The final panel data consisted of 850 posts observed for 14 times (11,894 observations in
total[1]). Table I shows the brief definition of all variables; Table II shows the descriptive statistics of our final panel data; Table III shows the correlation matrix of key variables in our analysis.

4.2 Model specification
We utilized ordinary least squares regression to examine the plausible impacts in our hypotheses relying on the model specification in the following equation that is a contemporaneous system of equations consisting of three similar equations. The specifications are identified to estimate the main effect of message framing (i.e. collective sentiments) on each kind of users’ engagement behavior, and the moderating influence of users’ thumbs-up and reply on such causal relationships:

\[
\begin{align*}
\ln(LFreq_{it}) + \ln(CFreq_{it}) + \ln(SFreq_{it}) &= \alpha_i + \beta_1 PosFreq_{it} \\
&+ \beta_2 NeuFreq_{it} + \beta_3 NegFreq_{it} + \beta_4 TRatio_{(POS)it} \\
&+ \beta_5 TRatio_{(NEU)it} + \beta_6 TRatio_{(NEG)it} \\
&+ \beta_7 TRatio_{(POS)it} \times PosFreq_{it} \\
&+ \beta_8 TRatio_{(NEU)it} \times NeuFreq_{it} \\
&+ \beta_9 TRatio_{(NEG)it} \times NegFreq_{it} \\
&+ \beta_{10} RepRatio_{(POS)it} + \beta_{11} RepRatio_{(NEU)it} \\
&+ \beta_{12} RepRatio_{(NEG)it} + \beta_{13} RepRatio_{(POS)it} \\
&\times PosFreq_{it} + \beta_{14} RepRatio_{(NEU)it} \times NeuFreq_{it} \\
&+ \beta_{15} RepRatio_{(NEG)it} \times NegFreq_{it} \\
&+ \gamma_1 \ln(PostAge_{it}) + \gamma_2 \ln(PageFans_{it}) \\
&+ \gamma_3 PostType_i + \gamma_4 Brand_i + \theta_i + \phi_i + \epsilon_{it},
\end{align*}
\]

(3)

where \(LFreq_{it}, CFreq_{it}\), and \(SFreq_{it}\) are the frequency of likes, comments and shares of post \(i\) at time \(t\), respectively. \(PosFreq_{it}\) is the frequency of positive comments in post \(i\) at time \(t\);

<table>
<thead>
<tr>
<th>Variables</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>(LFreq_{it})</td>
<td>The frequency of likes in post (i) at time (t) in thousands</td>
</tr>
<tr>
<td>(CFreq_{it})</td>
<td>The frequency of comments in post (i) at time (t) in thousands</td>
</tr>
<tr>
<td>(SFreq_{it})</td>
<td>The frequency of shares in post (i) at time (t) in thousands</td>
</tr>
<tr>
<td>(PosFreq_{it})</td>
<td>The frequency of positively framed comments in post (i) at time (t)</td>
</tr>
<tr>
<td>(NeuFreq_{it})</td>
<td>The frequency of neutrally framed comments in post (i) at time (t)</td>
</tr>
<tr>
<td>(NegFreq_{it})</td>
<td>The frequency of negatively framed comments in post (i) at time (t)</td>
</tr>
<tr>
<td>(TRatio_{(POS)it})</td>
<td>The average thumbs-up count related to the positively framed comments in post (i) at time (t)</td>
</tr>
<tr>
<td>(TRatio_{(NEU)it})</td>
<td>The average thumbs-up count related to the neutrally framed comments in post (i) at time (t)</td>
</tr>
<tr>
<td>(TRatio_{(NEG)it})</td>
<td>The average thumbs-up count related to the negatively framed comments in post (i) at time (t)</td>
</tr>
<tr>
<td>(RepRatio_{(POS)it})</td>
<td>The average reply count related to the positively framed comments in post (i) at time (t)</td>
</tr>
<tr>
<td>(RepRatio_{(NEU)it})</td>
<td>The average reply count related to the neutrally framed comments in post (i) at time (t)</td>
</tr>
<tr>
<td>(RepRatio_{(NEG)it})</td>
<td>The average reply count related to the negatively framed comments in post (i) at time (t)</td>
</tr>
<tr>
<td>(PostType_i)</td>
<td>The type of content of post (i)</td>
</tr>
<tr>
<td>(PostAge_{it})</td>
<td>The number of days between the creation time of post (i) and the observation time (t)</td>
</tr>
<tr>
<td>(PageFans_{it})</td>
<td>The number of fans of the brand page that published post (i) at time (t) in thousands</td>
</tr>
<tr>
<td>(Brand_i)</td>
<td>The brand that published the post (i) on its page</td>
</tr>
</tbody>
</table>

**Note:** The observation time \((t)\) in our study is equal to a half-day or 12 h period
NegFreq\textsubscript{it} is the number of negative comments in post \textit{i} at time \textit{t}, and finally, NeuFreq\textsubscript{it} is the number of neutral comments in post \textit{i} at time \textit{t}. TRatio\textsubscript{POS}\textsubscript{it}, TRatio\textsubscript{NEU}\textsubscript{it} and TRatio\textsubscript{NEG}\textsubscript{it} are the average thumbs-up count given to positively framed, neutrally framed and negatively framed comments in post \textit{i} at time \textit{t}, respectively. RepRatio\textsubscript{POS}\textsubscript{it}, RepRatio\textsubscript{NEU}\textsubscript{it} and RepRatio\textsubscript{NEG}\textsubscript{it} are the average reply count related to positively framed, neutrally framed and negatively framed comments in post \textit{i} at time \textit{t}, respectively. Also, PostAge\textsubscript{it} refers to the number of days between the time of data collection and the creation time of post \textit{i} at time \textit{t}. PageFans\textsubscript{it} refers to the number of fans of the brand page related to the post \textit{i} at time \textit{t}. We also controlled for the type of content (i.e. PostType\textsubscript{i}), brand-specific (i.e. Brand\textsubscript{i}), post-specific (\(\varphi\)) and time-invariant (\(\theta\)) heterogeneity to control for any unobserved or omitted variables related to brands, posts and time. Finally, \(\varepsilon_{it}\) is the error term in the presented equation.

5. Results
5.1 Main analysis and results
The results of our estimations for liking behavior are reported in Table IV. The main effects of collective sentiments are reported in Model (1); Models (2) and (3) report the results with
<table>
<thead>
<tr>
<th>Variables</th>
<th>Model (1) Fixed-effects only sentiments</th>
<th>Model (2) Fixed-effects sentiments and ratios</th>
<th>Model (3) Fixed-effects full model</th>
<th>Model (4) Hausman–Taylor IV full model</th>
<th>Model (5) SUR full model</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\text{PosFreq}_{it})</td>
<td>0.0186*** (0.0042)</td>
<td>0.0135*** (0.0020)</td>
<td>0.0170*** (0.0028)</td>
<td>0.0172*** (0.0011)</td>
<td>0.0099*** (0.0004)</td>
</tr>
<tr>
<td>(\text{NeuFreq}_{it})</td>
<td>0.0009 (0.0046)</td>
<td>0.0014 (0.0034)</td>
<td>0.0008 (0.0036)</td>
<td>0.0001 (0.0027)</td>
<td>0.0155*** (0.0018)</td>
</tr>
<tr>
<td>(\text{NegFreq}_{it})</td>
<td>0.0137*** (0.0038)</td>
<td>0.0145*** (0.0032)</td>
<td>0.0189*** (0.0036)</td>
<td>0.0194*** (0.0018)</td>
<td>-0.0078*** (0.0012)</td>
</tr>
<tr>
<td>(\text{TRatio}_{POS it})</td>
<td>0.1627** (0.0559)</td>
<td>0.1655** (0.0583)</td>
<td>0.1763*** (0.0167)</td>
<td>0.1216*** (0.0167)</td>
<td>0.0132 (0.0083)</td>
</tr>
<tr>
<td>(\text{TRatio}_{NEU it})</td>
<td>0.0127 (0.0140)</td>
<td>0.0190 (0.0150)</td>
<td>0.0202*** (0.0072)</td>
<td>0.0132 (0.0083)</td>
<td>0.0132 (0.0083)</td>
</tr>
<tr>
<td>(\text{TRatio}_{NEG it})</td>
<td>0.0326 (0.0220)</td>
<td>0.0538** (0.0267)</td>
<td>0.0550*** (0.0129)</td>
<td>0.1169*** (0.0110)</td>
<td>0.0132 (0.0083)</td>
</tr>
<tr>
<td>(\text{TRatio}<em>{POS it} \times \text{PosFreq}</em>{it})</td>
<td>0.0023* (0.0009)</td>
<td>-0.0022*** (0.0007)</td>
<td>-0.0019*** (0.0005)</td>
<td>-0.0011*** (0.0002)</td>
<td>-0.0011*** (0.0002)</td>
</tr>
<tr>
<td>(\text{TRatio}<em>{NEU it} \times \text{NeuFreq}</em>{it})</td>
<td>0.0076 (0.0141)</td>
<td>0.0156 (0.0154)</td>
<td>0.0165*** (0.0091)</td>
<td>0.0174** (0.0174)</td>
<td>0.0067*** (0.0002)</td>
</tr>
<tr>
<td>(\text{TRatio}<em>{NEG it} \times \text{NegFreq}</em>{it})</td>
<td>0.0221* (0.0085)</td>
<td>0.0169** (0.0084)</td>
<td>0.0185*** (0.0024)</td>
<td>0.0420*** (0.0102)</td>
<td>0.0420*** (0.0102)</td>
</tr>
<tr>
<td>(\text{RepRatio}_{POS it})</td>
<td>0.1242** (0.0384)</td>
<td>0.1229*** (0.0062)</td>
<td>0.0511*** (0.0104)</td>
<td>0.0511*** (0.0104)</td>
<td>0.0511*** (0.0104)</td>
</tr>
<tr>
<td>(\text{RepRatio}_{NEU it})</td>
<td>0.1242** (0.0384)</td>
<td>0.1229*** (0.0062)</td>
<td>0.0511*** (0.0104)</td>
<td>0.0511*** (0.0104)</td>
<td>0.0511*** (0.0104)</td>
</tr>
<tr>
<td>(\text{RepRatio}<em>{NEG it} \times \text{PosFreq}</em>{it})</td>
<td>-0.0020 (0.0012)</td>
<td>-0.0030*** (0.0008)</td>
<td>-0.0018*** (0.0003)</td>
<td>-0.0018*** (0.0003)</td>
<td>-0.0018*** (0.0003)</td>
</tr>
<tr>
<td>(\text{RepRatio}<em>{NEU it} \times \text{NeuFreq}</em>{it})</td>
<td>0.0004 (0.0004)</td>
<td>-0.0003 (0.0004)</td>
<td>0.0004 (0.0004)</td>
<td>0.0004 (0.0004)</td>
<td>0.0004 (0.0004)</td>
</tr>
<tr>
<td>(\text{RepRatio}<em>{NEG it} \times \text{NegFreq}</em>{it})</td>
<td>-0.0004 (0.0004)</td>
<td>-0.0003 (0.0004)</td>
<td>0.0004 (0.0004)</td>
<td>0.0004 (0.0004)</td>
<td>0.0004 (0.0004)</td>
</tr>
</tbody>
</table>

**Notes:** Control variables are including \(\text{PostAge}, \text{PageFans}, \text{PostType},\) and \(\text{Brand}\). The estimations related to control variables are not included in the table to save space. Model (1) reports the base model estimations that only account for the collective sentiments. Model (2) reports the estimations for collective sentiments along with thumbs-up and reply ratios. Model (3) reports the estimations for the full model as represented in Equation (3) with the inclusion of two-way interaction terms. Model (4) reports the robust results to the potential endogeneity issue of our contemporaneous equations. Model (5) reports the robust results to the potential correlation of error term across equations in our system with the correction for autocorrelation. Heteroskedastic robust standard errors in parentheses in Model (1), Model (2) and Model (3). *0.05; **0.01; ***0.001; ****0.10.
the inclusion of the main effects of thumbs-up ratio and reply ratio, and their interactions with collective sentiments, respectively. The coefficients of the main effects of positive and negative sentiments are significant in all three models. Although both positively and negatively framed comments have a positive impact on liking behavior, this impact is higher for negatively framed comments in full model specifications. On the other hand, results show that neutrally framed comments do not have a significant impact on liking behavior.

Moreover, results show that higher thumbs-up ratio for both neutrally and negatively framed comments hinders the liking behavior. This means if users leave a thumbs-up to neutrally or negatively framed comments then they are likely to negatively moderate the influence of neutrally or negatively framed comments on user’s liking behavior, respectively. Although negatively framed comments increase liking behavior, receiving more thumbs-up ratio can deteriorate that influence. Surprisingly, replying to neutrally framed comments might counteract the moderation impact of users’ thumbs-up on liking behavior regarding neutrally framed comments. Finally, positively framed comments that gain a high reply ratio might deteriorate the influence of such comments on liking behavior.

5.2 Robustness checks
The contemporaneous nature of our equations can cause an endogeneity issue that is due to the simultaneity of our model specifications; there is a potential joint determination of explanatory variables with the dependent variables in our model. For example, an increased engagement level can potentially affect the extent of online social interactions (e.g. the frequency of collective sentiments) on brand posts. Simply put, endogeneity is caused by a correlation between the error term and an endogenous variable (Suvankulov et al., 2012). As a result, our primary estimations might be biased. To address this plausible bias in the estimation of our full model we use an instrumental variable (IV) technique on our panel data. A Hausman–Taylor IV model for panel data (Hausman and Taylor, 1981) is used to tackle the endogeneity bias in this study (see Suvankulov et al., 2012, for an overview of the Hausman–Taylor IV model that we have adopted to address the endogeneity issue). The endogeneity issue can also happen because of omitted variables. In this regard, we included both brand page and post-specific fixed effects along with time-invariant fixed effects to control for the unobserved heterogeneity in our primary estimations. The column related to Model (4) in all Tables IV–VI reports the robust results regarding endogeneity bias. Moreover, since we have a system of three equations, the error terms might be correlated across equations. This can cause an estimation bias when equations in the system are estimated...
<table>
<thead>
<tr>
<th>Variables</th>
<th>Model (1)</th>
<th>Model (2)</th>
<th>Model (3)</th>
<th>Model (4)</th>
<th>Model (5)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Fixed-effects only sentiments</td>
<td>Fixed-effects sentiments and ratios</td>
<td>Fixed-effects full model</td>
<td>Hausman–Taylor IV full model</td>
<td>SUR full model</td>
</tr>
<tr>
<td>PosFreq_{it}</td>
<td>0.0232*** (0.0042)</td>
<td>0.0171*** (0.0033)</td>
<td>0.0132* (0.0062)</td>
<td>0.0139*** (0.0037)</td>
<td>0.0093*** (0.0007)</td>
</tr>
<tr>
<td>NeuFreq_{it}</td>
<td>-0.0131 (0.0094)</td>
<td>-0.0085 (0.0100)</td>
<td>-0.0026 (0.0115)</td>
<td>-0.0036 (0.0087)</td>
<td>0.0178*** (0.0031)</td>
</tr>
<tr>
<td>NegFreq_{it}</td>
<td>0.0464*** (0.0065)</td>
<td>0.0443*** (0.0069)</td>
<td>0.0512*** (0.0075)</td>
<td>0.0513*** (0.0057)</td>
<td>0.0060* (0.0022)</td>
</tr>
<tr>
<td>TRatio_{POSit}</td>
<td></td>
<td>0.0045 (0.3080)</td>
<td>0.0117 (0.0324)</td>
<td>0.0144 (0.0515)</td>
<td>0.0023 (0.0323)</td>
</tr>
<tr>
<td>TRatio_{NEUit}</td>
<td></td>
<td>0.0017* (0.0460)</td>
<td>0.1173* (0.0478)</td>
<td>0.1167*** (0.0236)</td>
<td>0.0316** (0.0144)</td>
</tr>
<tr>
<td>TRatio_{NEGit}</td>
<td></td>
<td>0.0324 (0.0363)</td>
<td>0.0597*** (0.0310)</td>
<td>0.0606 (0.0420)</td>
<td>0.1141*** (0.0192)</td>
</tr>
<tr>
<td>TRatio_{POSit} × PosFreq_{it}</td>
<td></td>
<td>-0.0007 (0.0009)</td>
<td>-0.0003 (0.0008)</td>
<td>0.0004*** (0.0001)</td>
<td></td>
</tr>
<tr>
<td>TRatio_{NEUit} × NeuFreq_{it}</td>
<td></td>
<td>-0.0086*** (0.0019)</td>
<td>-0.0075*** (0.0021)</td>
<td>-0.0004 (0.0003)</td>
<td></td>
</tr>
<tr>
<td>RepRatio_{POSit}</td>
<td>-0.1633 (0.1067)</td>
<td>-0.1735 (0.1111)</td>
<td>-0.1717*** (0.0297)</td>
<td>0.0172 (0.0304)</td>
<td></td>
</tr>
<tr>
<td>RepRatio_{NEUit}</td>
<td>0.0415*** (0.0093)</td>
<td>0.0310*** (0.0088)</td>
<td>0.0321*** (0.0111)</td>
<td>0.0375* (0.0178)</td>
<td></td>
</tr>
<tr>
<td>RepRatio_{NEGit}</td>
<td>0.0616 (0.0388)</td>
<td>0.0585 (0.0392)</td>
<td>0.0588*** (0.0202)</td>
<td>0.0131 (0.0181)</td>
<td></td>
</tr>
<tr>
<td>RepRatio_{POSit} × PosFreq_{it}</td>
<td></td>
<td>0.0032 (0.0029)</td>
<td>0.0021 (0.0025)</td>
<td>-0.0012* (0.0005)</td>
<td></td>
</tr>
<tr>
<td>RepRatio_{NEUit} × NeuFreq_{it}</td>
<td></td>
<td>0.0049*** (0.0013)</td>
<td>0.0044* (0.0021)</td>
<td>0.0004 (0.0008)</td>
<td></td>
</tr>
<tr>
<td>RepRatio_{NEGit} × NegFreq_{it}</td>
<td></td>
<td>-0.0003 (0.0004)</td>
<td>-0.0003 (0.0014)</td>
<td>0.0022*** (0.0007)</td>
<td></td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>11,894</td>
<td>11,894</td>
<td>11,894</td>
<td>11,894</td>
<td>11,894</td>
</tr>
<tr>
<td>Adj. R²</td>
<td>0.9928</td>
<td>0.9929</td>
<td>0.9929</td>
<td>0.9929</td>
<td>0.9824</td>
</tr>
</tbody>
</table>

**Notes:** Control variables are including PostAge, PageFans, PostType, and Brand. The estimations related to control variables are not included in the table to save space. Model (1) reports the base model estimations that only account for the collective sentiments. Model (2) reports the estimations for collective sentiments along with thumbs-up and reply ratios. Model (3) reports the estimations for the full model as represented in Equation (3) with the inclusion of two-way interaction terms. Model (4) reports the robust results to the potential endogeneity issue of our contemporaneous equations. Model (5) reports the robust results to the potential correlation of error term across equations in our system with the correction for autocorrelation. Heteroskedastic robust standard errors in parentheses in Model (1), Model (2) and Model (3). *0.05; **0.01; ***0.001; ****0.10
<table>
<thead>
<tr>
<th>Variables</th>
<th>Model (1) Fixed-effects only sentiments</th>
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<th>Model (4) Hausman–Taylor IV full model</th>
<th>Model (5) SUR full model</th>
</tr>
</thead>
<tbody>
<tr>
<td>PosFreq$_{it}$</td>
<td>0.0277*** (0.0063)</td>
<td>0.0211*** (0.0035)</td>
<td>0.0292*** (0.0049)</td>
<td>0.0297*** (0.0026)</td>
<td>0.0106*** (0.0006)</td>
</tr>
<tr>
<td>NeuFreq$_{it}$</td>
<td>-0.0035 (0.0078)</td>
<td>-0.0029 (0.0065)</td>
<td>-0.0012 (0.0069)</td>
<td>-0.0026 (0.0061)</td>
<td>0.0118*** (0.0029)</td>
</tr>
<tr>
<td>NegFreq$_{it}$</td>
<td>0.0209*** (0.0061)</td>
<td>0.0222*** (0.0053)</td>
<td>0.0298*** (0.0060)</td>
<td>0.0305*** (0.0040)</td>
<td>0.0038 (0.0020)</td>
</tr>
<tr>
<td>TRatio$_{POS, it}$</td>
<td>0.2322* (0.0952)</td>
<td>0.2376* (0.0993)</td>
<td>0.2516*** (0.0382)</td>
<td>0.041* (0.0165)</td>
<td>0.0166 (0.0297)</td>
</tr>
<tr>
<td>TRatio$_{NEU, it}$</td>
<td>0.1157*** (0.0665)</td>
<td>0.1600*** (0.0828)</td>
<td>0.1620*** (0.0294)</td>
<td>0.161*** (0.0177)</td>
<td>0.161*** (0.0177)</td>
</tr>
<tr>
<td>TRatio$_{NEG, it}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RepRatio$_{POS, it}$</td>
<td>-0.0022 (0.0238)</td>
<td>0.0158 (0.0264)</td>
<td>0.0173 (0.0208)</td>
<td>-0.0085 (0.0279)</td>
<td></td>
</tr>
<tr>
<td>RepRatio$_{NEU, it}$</td>
<td>0.0285** (0.0101)</td>
<td>0.0254* (0.0099)</td>
<td>0.0280*** (0.0078)</td>
<td>0.0477** (0.0164)</td>
<td></td>
</tr>
<tr>
<td>RepRatio$_{NEG, it}$</td>
<td>0.1481* (0.0667)</td>
<td>0.1462* (0.0674)</td>
<td>0.1456*** (0.0141)</td>
<td>0.0470* (0.0166)</td>
<td></td>
</tr>
<tr>
<td>RepRatio$<em>{POS, it} \times$ PosFreq$</em>{it}$</td>
<td>-0.0069 (0.0022)</td>
<td>-0.0073*** (0.0018)</td>
<td>-0.0017*** (0.0004)</td>
<td>-0.0001 (0.0007)</td>
<td></td>
</tr>
<tr>
<td>RepRatio$<em>{NEU, it} \times$ NeuFreq$</em>{it}$</td>
<td>0.0018*** (0.0011)</td>
<td>0.0019 (0.0015)</td>
<td>-0.0004 (0.0009)</td>
<td>0.0017*** (0.0006)</td>
<td></td>
</tr>
<tr>
<td>RepRatio$<em>{NEG, it} \times$ NegFreq$</em>{it}$</td>
<td>-0.0005 (0.0008)</td>
<td>-0.0004 (0.0009)</td>
<td>-0.0001 (0.0007)</td>
<td>0.0017*** (0.0006)</td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>42.48* (18.588)</td>
<td></td>
<td>162.05* (18.588)</td>
<td>16.05* (176.006)</td>
<td></td>
</tr>
</tbody>
</table>

**Notes:** Control variables are including PostAge, PageFans, PostType, and Brand. The estimations related to control variables are not included in the table to save space. Model (1) reports the base model estimations that only account for the collective sentiments. Model (2) reports the estimations for collective sentiments along with thumbs-up and reply ratios. Model (3) reports the estimations for the full model as represented in Equation (3) with the inclusion of two-way interaction terms. Model (4) reports the robust results to the potential endogeneity issue of our contemporaneous equations. Model (5) reports the robust results to the potential correlation of error term across equations in our system with the correction for autocorrelation. Heteroskedastic robust standard errors in parentheses in Model (1), Model (2) and Model (3). *0.05; **0.01; ***0.001; ****0.10.
independently. To tackle this issue, we applied seemingly unrelated regression (SUR) to estimate our system of equations at once. The column related to Model (5) in Tables IV–VI reports the robust results to contemporaneous correlation across equations in the system.

Accordingly, the main effects of positively and negatively framed comments remained consistent among almost all engagement behaviors, except for one case regarding the negatively framed comments and liking behavior. Hence, the SUR estimations show a significant but negative influence of negatively framed comments on liking behavior. Regardless, results show nearly full support for H1a and H1b. It is interesting that the SUR estimations show neutrally framed comments are likely to have a significant and positive impact on all engagement behaviors. However, we rather rely on the results held in common in the majority of cases. So, H1c is not supported according to the findings. The same situation exists for H2a regarding the moderation effect of thumbs-up ratio on the influence of positively framed comments on engagement behavior. Although the SUR estimations show the significance of such a moderation effect, other models reject H2a. On the other hand, results show strong support for H2b as thumbs-up ratio negatively moderates the influence of negatively framed comments on all engagement behaviors. Regarding H2c, the majority of model estimations report the existence of the significant and adverse moderation effect of thumbs-up ratio on the influence of neutrally framed comments on all engagement behaviors. However, the SUR estimations only support such a moderation effect only for liking behavior. Regarding H3a, the majority of model estimations report the existence of the significant and adverse moderating effect of reply ratio on the influence of positively framed comments on all engagement behaviors. However, this moderation effect is loosely supported for commenting behavior. More than half of the models show that reply ratio is likely to positively moderate the influence of neutrally framed comments on all engagement behaviors. However, this moderation effect is loosely supported regarding sharing behavior. Finally, only SUR estimations support H3c. Thus, we remain skeptical about such a moderation effect when the majority of model estimations reject H3c. The summary of all results related to our hypothesis testing is shown in Table VII.

6. Discussion and conclusions

6.1 Key findings

The findings of this study contribute to the existing literature related to message framing and SMBCs. First, unlike other studies in the context of SMBCs, this study explains the most
important type of online social interactions (i.e. WOM communication) and its impact on users’ engagement behavior on SMBCs using the theoretical lens of message framing and signaling theory. The findings of our study show that leaving more positively framed comments on a post by users helps the post to have a higher level of users’ engagement. In other words, positively framed comments are very likely to stimulate users to like, leave a comment on or share a post. When users are impartial about the content of a post or brand, and they leave neutrally framed comments on the post, it is not likely to help the post to obtain a higher level of engagement. On the other hand, when users leave more negatively framed comments on a post, it will be favorable for the post as it stimulates more users to leave comments on the post and raise the comments’ count. These results are consistent with the prior research indicating that both positive and negative WOM can evoke more consumer engagement in SMBCs (Relling et al., 2016). We showed how important the users’ approach to framing their comments are, and firms should pay attention to them. Our empirical analysis is also consistent with the findings of De Vries et al. (2012). Both studies support the fact that exposure to positive comments is positively related to the likes’ count. Also, they claimed that leaving negative comments on brand posts is positively related to comments’ count and our findings approve such a relationship. One explanation for the difference between engagement stimulated by positively and negatively framed signals is that the former leads to positive engagement while the latter brings about negative engagement (e.g. leaving a negative comment). Then, a post can have higher Facebook impressions, increasing the likelihood of exposure to more users and consequently might result in more like’s count and share’s count for the post.

More importantly, this research extends the theoretical explanations on the way message framing influences the human behavior by adding the moderation effect of “thumbs-up” that are indicators of endorsements or agreement with a message and the moderating effect of users’ “reply” that are proper signals of dynamics of a conversation. Our findings showed that if neutrally and negatively framed comments gain a higher thumbs-up count it will result in a lower engagement level. This finding fulfills our expectation about the fact that thumbs-up as an endorsing functionality not only increases the chances for putting those comments on top of the comments’ list but also deteriorating the chances of more engagement with the post via signaling and change of perception. Reply ratio might also have a positive and negative moderation effect on the influence of neutrally and positively framed comments on engagement behavior, respectively. Surprisingly, replying to neutrally framed comments might counteract the moderation impact of users’ thumbs-up on liking behavior regarding neutrally framed comments. This finding suggests that if neutrally framed comments receive thumbs-up from users, it is beneficial to start a conversation under those comments to minimize the plausible negative influence on engagement behaviors. The explanation for such effect is consistent with what Facebook has suggested after updating their News Feed algorithm at the beginning of 2018. A meaningful conversation on a post can be favorable for the engagement behavior, while findings suggest that this meaningful conversation might be better to be developed on neutrally framed comments rather than positively framed comments.

Reacting to users’ comments via a thumbs-up or leaving a reply is a sort of online social interaction that is investigated by a handful of studies and the existing knowledge about consequences of such an online behavior is confined to a limited understanding. Thus, it indeed needs to be investigated more. To the best of our knowledge, this might be the first study examining the role of users’ thumbs-up and reply as a moderator of the impact of message framing on users’ engagement behavior. Our findings on these moderation effects can be promising for developing new hypotheses and theoretical models in the context of online social interactions. However, these findings are preliminary, and these moderation effects may need to be investigated more in future research to develop a more mature body of knowledge on such online social interactions.
Overall, this study contributes to the prior literature of SMBC research and online social interactions. Also, this research broadens the existing knowledge related to the message framing in WOM communications.

6.2 Practical implications
As we explained before, the administrators of Facebook pages have no control over the order of comments under their posts. They can only hide or delete comments from a post which can be harmful to the firm if users notice it. The number of times users give a thumbs-up to comments or leave a reply to comments are determinatives of the position of the comment in the comments list. It is likely that a negatively framed comment with a high thumbs-up count sits on top of the comments list with the highest chance of exposure to users. Consequently, it is easier for users to read this comment and leave another thumbs-up or reply to it. Therefore, there is a high chance for this comment to remain on top of the list forever. In this regard, it is critical for firms to know the appropriate action in such a situation. What is a proper response to the negative WOM? It is true that a reasonable body of the literature suggested the negative WOM is harmful to firms. However, we believe this is a double-edged situation. The underlying phenomenon of this study can be either harmful or fruitful for firms. Negative WOM might lead to interesting positive outcomes. For instance, it is even possible that consumers try to defend a brand against negative publicity (Hassan and Casaló Ariño, 2016). There is also a famous statement that “any publicity is good publicity,” as Berger et al. (2010) suggested that negative publicity might increase the sales performance. However, we believe this problem needs more attention for research as the design of social media changes over time.

Also, social media is supposed to be a relatively low-cost marketing channel for promoting brands. In particular, SMBCs provide an opportunity for firms to start a meaningful conversation with their customers and garner users’ feedback. Firms desire to obtain the highest possible exposure (i.e. impressions) for their posts among users on social media. However, users are essential elements in acquiring higher impressions. When more users engage with a post, the post will reach to a broader audience, which is undoubtedly one of the critical aims of social media marketers. This unique trait in Facebook provides an opportunity for firms to attract more users to participate in their Facebook pages. So, even if users leave negatively framed comments on a post and these comments receive thumbs-up from users, it helps the post to reach a broader population of users. However, starting a meaningful conversation under those comments and increasing the reply count can counteract the plausible adverse moderation effect of users’ thumbs-up for negatively framed comments.

Our findings can be useful for the design of online brand communities particularly in the design of a sorting algorithm for comments. Also, our findings can be useful for improvement of social media management tools that are suggested to be effective for acquiring attitudinal loyalty and better word-of-mouth communications (Risius and Beck, 2015). Overall, this study presents important managerial implications by providing a clear understanding of users’ sentiment, thumbs-up, reply and engagement behavior.

6.3 Limitations and future directions
There are a few concerns about sampling issues in this study. Using a convenience sampling method for data collection in this study may have caused a sampling bias. However, it is a useful approach for preliminary investigations in social media. According to the real number of posts that brands publish on their Facebook page, the size of our sample is relatively small. Also, the sample is related to the brands in the technology sector, while other industry sectors are equally important. Also, any comment consisting of anything such as emoticons or hyperlinks but no text was removed from the analysis. Moreover, we only focused on those comments written in English language and other languages could be effective in the final results. Therefore, extending the idea of this research using a more comprehensive and
reliable sample can be a direction for future studies. Investigation of other social media platforms can also be an excellent opportunity for future research to show the generalizability of the findings. Facebook is a very dynamic platform, and it adds new features from time to time. Accordingly, it is hard to address all these new features in one single study. For instance, since the time of this study, Facebook has introduced new engagement features (i.e. emoji-based emotional reactions). Future research can consider these new features to investigate whether they cause any change in the highlighted online social interactions on Facebook. Further, impressions can be a useful measure for evaluating the effectiveness of social media marketing on Facebook. However, this study aimed to predict engagement behavior led by online social interactions rather than predicting impressions. One reason is that impressions data was not available as it needs special access from managers of brand pages. Future research can focus on impressions as a measure of social media marketing effectiveness on Facebook or other social media platforms. Moreover, Facebook does not allow for the collection of any user-related information via its API. So we could not conduct a more in-depth user-level analysis. In this regard, the dynamics of conversations (i.e. commenters and repliers) such as participation of new users and the return of those who already participated in the conversation, and the size of their network that can identify the extent of exposure of brand posts is an excellent direction for future research[2].

Notes

1. There were very few observations missing from the panel data due to the removal of the corresponding brand post(s) by the administrators of the page(s) during data collection period.
2. We appreciate an anonymous reviewer who suggested this idea that can be considered for future research as we did not have access to the user information on Facebook due to privacy policies.

References


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