Engagement by Design: An Empirical Study of the "Reactions" Feature on Facebook Business Pages

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Abstract

We study the impact and interplay of social design features on the engagement behaviors toward user-generated content on Facebook business pages. By examining the introduction of the "Reactions" feature on Facebook, we aim to understand how the introduction of a new engagement feature affects the overall engagement activities and the use of existing engagement features. We found evidence of a positive effect of Reactions on overall engagement levels. Furthermore, the introduction of the Reactions feature had heterogeneous effects on the use of existing engagement features. Posts that received Reactions also ended up receiving more Likes and Comments than what they *would have* received before the feature change. However, the opposite is true for posts that received no Reactions, although the effect sizes were small. These effects were detected within the first four weeks after the feature introduction, and persisted after six months, indicating long-term structural changes in users' engagement behaviors.

Keywords: social computing, social media, user engagement, user-generated content, feature design, Facebook business pages, heterogeneous effects

1. INTRODUCTION

Businesses and organizations in the past decade are increasingly and profoundly revolutionized by online platforms, which have been a strong force that connects individuals, fosters innovation, and drives economic development. Much of the online platforms' power depends on social interactions (Van Alstyne et al. 2016; Erickson and Kellogg 2000; Lin 2014), which are enabled and shaped by various design features. An analysis of design features at several major websites revealed a clear proliferation of social features (Curty and Zhang 2013). From popular social media sites like Facebook and Twitter to social commerce and sharing economy platforms like Amazon and Uber, many platforms have introduced social features to facilitate connections, conversations, and a sense of community among users (Huang and Benyoucef 2013; Joinson 2008). Meanwhile, the primary focus of system and platform design has shifted from designing for usability (Gould and Lewis 1985) to designing for sociability and user engagement (Kraut et al. 2011; O'Brien and Toms 2008; Preece 2001; Whittaker 2013).

Feature design represents an important strategic decision of an online platform, and has significant impact on its user activities and interactions (Aral et al. 2013). A significant challenge in designing for user engagement is the trade-off between the richness and complexity of features. On one hand, platforms may want to offer a rich set of features because users may request new capabilities, and more features provide a greater variety of ways for users to participate. For example, Facebook introduced the iconic "Like" button in 2009 to allow users to express their affection for certain content (Schöndienst et al. 2012) and rolled out the "Reactions" feature in 2016. Social media platforms like Twitter, Instagram, and LinkedIn have similarly introduced Like and Comment features. Some other platforms such as YouTube, Reddit, and StackOverflow also introduced a "Dislike" button.

On the other hand, greater feature richness is often associated with higher complexity for end users, and too many features can become "too much a good thing" and cause feature creep and feature fatigue (Thompson et al. 2005). When users get overwhelmed by complex features, they may experience attention depletion and greater cognitive burden, and, as a result, may not use the features at all or as intended. There has been research evidence highlighting the importance of prioritizing features and the unintended consequences of new feature offerings. For example, research of website navigation system design (Webster and Ahuja 2006) showed that simple navigation designs sometimes work better than complex designs in engaging and assisting users. Experiments of online community design (Ren et al. 2012) showed that introductions of new features that challenge or violate users' existing perceptions and experiences with an online community might reduce user engagement.

The rising importance of online platforms for businesses and organizations demands a deeper understanding of the interplay among multiple design features and, in particular, how newly introduced features interact with preexisting features to shape user behaviors (Matthews et al. 2014). In this paper, we consider two research questions: (1) *how does the introduction of a new engagement feature on social media affect overall engagement, and (2) how does the new feature affect the use of existing engagement features?* Answers to these questions are unclear. On one hand, it is possible that different engagement features are designed to provide distinct functionalities, and users choose the features that best fit their goals and preferences. On the other hand, different engagement features may be interdependent in the sense that the use of one feature may facilitate or substitute the use of other features.

We aim to address these questions by studying the introduction of the Reactions feature on Facebook business pages. Facebook rolled out the "Reactions" feature on its platform on February 24, 2016. With the new feature, users can engage with Facebook posts by clicking one of the five Reactions buttons, which are *love*, *haha*, *wow*, *sad*, and *angry*. This feature change attracted much attention from businesses and organizations, with a keen interest in understanding its implications for brands and marketers (Brink 2016), and how it may affect user engagement and use of existing features such as Likes and Comments (Shah 2018, HubSpot 2016).

Facebook business pages are managed by companies and organizations to engage and interact with their fans on Facebook. The pages are often used to broadcast marketing messages, foster a community of loyal customers or supporters, and facilitate interactions among customers and stakeholders (Goh et al. 2013; Dholakia and Durham 2010). Visitors to Facebook business pages can view both company-generated content and user-generated content, and engage with the content via multiple features such as Likes, Comments, and Reactions. Figure 1 shows an example user post on Walmart's Facebook business page and the different engagement features that can be used to engage with the post (the Reactions feature is visible when hovering over the Like button).

Figure 1. An Example User Post on Facebook Business Pages and Engagement Features

Note. The left panel shows the design of Reactions feature. Reaction buttons will appear when the mouse hovers over the Like button. The right panel shows a user post that received some Likes, Comments, and Reactions.

We chose Facebook business pages as our research context for two reasons. First, Facebook business pages represent one of the most prominent social media marketing channels and used by many organizations worldwide. User engagement on Facebook business pages has been linked to increases in brand loyalty, purchase expenditures, and firm profitability (Hoffman and Fodor 2010; Dessart et al. 2015; Goh et al. 2013; Rishika et al. 2013). It is therefore a natural context to study how design features affect user engagement with businesses and organizations on social media. Second, Facebook business pages represent an empirical setting where most interactions occur among strangers and are driven by measurable characteristics of the pages and of the content. This helps mitigate the unobserved influence of Facebook's proprietary news feed algorithm or the users' personal social networks, and therefore allows us to draw more robust conclusions. While the business pages are populated with both company-generated and user-generated content, in this paper, we focus on *user-generated content* (hereafter referred to as "user posts"), because user posts outweigh company-generated posts in both volume and impact on consumer purchase behaviors (Goh et al. 2013). Studying user posts and the associated engagement activities has significant practical relevance to businesses and organizations.

We collected all user posts on the business pages of 29 Fortune 500 companies across 6 consumer-oriented industries, generated 6 months before and 6 months after the introduction of the Reactions feature. We compared user posts created before the feature change with those created after the change, to understand how the introduction of the Reactions feature affected overall engagement with user posts. We then split the user posts that were generated *after* the feature change into two distinct groups: (1) those that received Reactions and (2) those that did not receive any Reactions, and examined the impact of the Reactions feature on each of the two groups. To account for endogeneity in receiving (or not receiving) Reactions, we relied on matching methods (including propensity score matching and coarsened exact matching) to construct a matched sample of posts before and after the feature change with comparable characteristics. To examine the impact of Reactions on the use of existing engagement features, we then estimated whether user posts with (or without) Reactions end up receiving more or fewer Likes and Comments than what they would have received before the feature change.

Our study has several key findings. First, the introduction of the Reactions feature increased the overall engagement received by an average user post on the Facebook business pages. Second, the introduction of the Reactions feature led to greater disparity among posts in the amount of engagement they received. Specifically, the effects of the Reactions feature on existing features were heterogeneous and depended on whether the post had received any Reactions. User posts that received at least one Reaction ended up receiving more Likes and more Comments than what they would have received before the feature change. In contrast, user posts that were created after the feature change yet did not receive any Reactions ended up receiving fewer Likes and fewer Comments than what they would have received before the feature change, although the effect sizes were small. Third, these effects were detected within 1 month after the feature change, and also persisted after 6 months, suggesting that the new feature led to long-term, lasting changes in engagement patterns. Finally, to assess the generalizability of our findings, we complemented the analyses of Facebook business pages with an analysis of a similar Reactions feature that was introduced on GitHub issues page and found similar patterns.

Our work contributes several new insights to the human-computer interaction and social media literature. In the area of designing social features to facilitate user-generated content and social interactions (Lindtner et al. 2011), our study is one of the first attempts to study the dynamic relationships among social media engagement features. We theorize and empirically demonstrate that the introduction of a new engagement feature is not merely an additional avenue for user expression and interaction, but that it can also lead to structural changes in engagement behaviors. Our work provides practical implications for several stakeholders. For Facebook, our paper offers important empirical evidence of how the new feature is actually being used. For organizations that manage their Facebook business pages, our paper uncovers the changing dynamics of user engagement behaviors, which can facilitate more effective cultivation of engagement activities on their pages.

2. LITERATURE REVIEW AND THEORY DEVELOPMENT

2.1. Social Media Engagement Features

Engagement is defined as an individual's participation and connection with an organization's offerings and activities initiated by either the individual or the organization (Vivek et al. 2012). Likes, Comments, and the newly introduced Reactions are all instances of engagement features designed to enable users to interact with one another and to express their opinions about content. In the social media and online community literature, these engagement features represent an important type of technology capability often referred to as metavoicing (Majchrzak et al. 2013; Dong et al. 2016; Nan and Lu 2014). Metavoicing allows users to engage in online conversations by reacting to other users' presence, content, and activities. By pooling individual users' opinions, metavoicing facilitates the construction of metaknowledge that may signal the quality of the content (Majchrzak et al. 2013).

Different forms of engagement features are typically designed to facilitate different engagement goals. Taking Facebook as an example, "Like" is designed to be a one-click, lightweight feedback to demonstrate affection and enjoyment of the content (Chan 2009). In fact, in Facebook's announcement to introduce the "Like" button, it was compared to the star ratings people give on review websites (Chan 2009). In comparison, "Comment" is designed to express more substantive opinions and "longer accolades" (Gerlitz and Helmond 2011). It was analogous to textual reviews on review websites (Chan 2009). Finally, the new Reactions feature is designed to "give [users] more ways to share [their] reaction to a post in a quick and easy way" (Facebook Newsroom 2016). In other words, the Reactions feature expands the scope of emotions conveyed by a one-click feedback. Beyond the affirmative emotion represented by Likes, users can now express other emotions, including more granular positive emotions (*love*, *haha*, and *wow*) as well as negative emotions (*sad* and *angry*). Meanwhile, the Reactions feature maintains the lightweight nature of engagement (similar to Like), as compared to Comment.

Prior literature on social media engagement typically treats engagement features as given and focuses primarily on studying the antecedents or consequences of user engagement behaviors (e.g., Andalibi et al. 2017; Ames and Naaman 2007; Lampe et al. 2007; Burke et al. 2010; Goh et al. 2013; Dessart et al. 2015; Luo et al. 2013; Rishika et al. 2013; Miller and Tucker 2013). Our work is different in that we view engagement features as dynamic, and examine how user engagement behaviors change when a new engagement feature is introduced. In other words, we study the interplay among multiple design features, which is important for understanding of how individuals and organizations combine the use of multiple features or tools in their interactive activities (Matthews et al. 2014).

2.2. Impact of Reactions Feature on Overall Engagement

We consider the impact of the Reactions feature on overall engagement by characterizing different engagement behaviors on two dimensions: the level of *cognitive* effort required (Shevlin 2007; Oestreicher-Singer and Zalmanson 2013) and the *emotional* states expressed (Brodie et al. 2011). Liking, as a "lightweight, one-click feedback action" (Scissors et al. 2016), requires low cognitive effort and represents a low level of involvement with the content. In contrast, commenting is a deliberate form of "composed communication" that requires high cognitive effort (Burke and Kraut 2014; Swani et al. 2013). In terms of emotional complexity, liking is mainly used to express positive, affirmative emotions such as agreement, empathy, acceptance, or awareness (Scissors et al. 2016), whereas commenting can express much more complicated emotions.

Reactions, as a new feature, "inherits" the low cognitive effort of liking while supporting the expression of greater emotional complexity than liking. Hence, we speculate that the introduction of the Reactions feature makes it easier for users to engage with the content and hence increases their likelihood of engagement. For example, without the Reactions feature, users may not engage with certain content at all if they do not want to spend the effort to compose a comment and also feel that liking is not an appropriate response (e.g., towards a sad or unfortunate event). With the Reactions feature, these users can now engage with the content with a one-click reaction to convey the appropriate emotion. As such, the introduction of the Reactions feature is likely to increase overall level of engagement.

Meanwhile, to fully understand how the Reactions feature affects engagement, we also need to characterize its impact on the use of existing engagement features (i.e., Likes and Comments). We argue that it is possible for the Reactions feature to both *substitute* and *reinforce* Likes and Comments, and we explain the potential mechanisms behind each possibility.

2.3. The Substitution Effect

There are reasons to believe that the newly introduced Reactions may substitute some Likes and Comments, so that, after the introduction of the Reactions feature, the number of Likes and the number of Comments for a user post that has received Reactions may *decrease*. This happens because certain user responses previously expressed via Likes or Comments can now be directly and more appropriately expressed via Reactions. We suspect that the substitution effect mainly happens at the individual user level, when an individual user's use of Reactions affects his/her use of Likes and Comments. For instance, a user who wants to express a strong emotion of awe towards a post would have needed to provide a Like and/or Comment for the post prior to the introduction of Reactions, but can now just click the "wow" button. Similarly, a user who wants to express sympathy towards a post can now simply click the "sad" button, instead of writing a comment or (potentially inappropriately) clicking the Like button.

The substitution effect can also be understood through the perspective of the *Emotion Regulation theory*. According to the Emotion Regulation theory (Gross 1998), being able to clearly articulate one's emotion can help individuals make sense of their emotions and experiences, which subsequently leads to improved interpersonal relationships (Gross and John 2003). Therefore, having access to an engagement feature that enables easy expression of granular emotions is likely to substitute the need for other engagement features with lower granularity. Compared to Likes, Reactions allow users to express more granular emotions with similar levels of effort. Thus, we expect users to use Reactions, instead of Likes, when they want to convey more sophisticated emotions that are better captured by the Reactions feature than the Like feature. Meanwhile, Reactions may also reduce the use of Comments, when Reactions allow users to express similar emotions and opinions as Comments yet with substantially lower effort.

It is worth noting that the substitution effect may also be part of Facebook's motivation to introduce the Reactions feature. When the Like button was introduced in 2009, it was Facebook's intention to use it to replace short, affirmative Comments such as "Awesome!" or "Congrats!" (Chan 2009; Gerlitz and Helmond 2013). Although empirical evidence is not available to test whether there was indeed substitution of Comments by Likes, it is logically plausible that users would switch to a new engagement feature when the new feature is easier to use or better at expressing their emotions or opinions. Similarly, it was Facebook's intention to use the Reactions feature to provide users with new ways to quickly and easily respond to posts and express a wider variety of emotions, such as empathy and negative feelings.[1] As a result, users may see less need to use Likes or Comments when they want to express the types of emotions associated with the Reactions feature.

2.4. The Reinforcement Effect

It is also possible that Reactions may reinforce Likes and Comments, causing a post to receive more Likes

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[1] https://www.forbes.com/sites/kathleenchaykowski/2016/02/24/facebook-no-longer-just-has-a-like-button-thanks-to-global-launch-of-emoji-reactions

and more Comments than it would have, had there been no Reactions.

One possible driver for the reinforcement effect is the signaling mechanism when there is attention scarcity, as users on Facebook take other users' actions as signals to decide where to focus their attention. The abundance of user-generated content on review websites, social media platforms, and online communities implies that the content often needs to compete for users' attention (Wang et al. 2013; Shen et al. 2015; Iyer and Katona 2015). Such attention competition can be particularly intense for user posts on Facebook business pages, because the Facebook business page of a large company can receive hundreds of user posts on a daily basis, whereas visitors to the page typically spend only a few minutes during each visit (Yang et al. 2019). Therefore, on Facebook business pages, the abundance of user posts and limited attention that users can spare suggest that users may rely on certain signals to choose which content to consume and engage with. We argue that receiving Reactions can serve as a signal in two ways: (1) by adding to the *amount* of engagement that a post receives; and (2) by providing *useful information* about the content.

First, receiving Reactions adds to the overall amount of engagement received by a post. In the user-generated content literature, the amount of engagement has been frequently used as a signal of the popularity or quality of the content. De Vries et al. (2012) used the number of Likes and the number of Comments received by a brand post to measure the popularity of that post. Similarly, Khobzi et al. (2017) measured the counts of Likes, Comments, and Shares to assess the dissemination of a post among users. Schöndienst et al. (2012) showed that when a post about products and services received more Likes, people perceived the quality of products and services to be more superior. Therefore, users on Facebook business pages may treat the number of Reactions (along with Likes and Comments) that a post has received as a signal of the quality or popularity of the post, and focus their attention on a subset of posts that have received some engagement. Furthermore, Reactions allow users to express a variety of emotions with a simple click. As a result, some posts that might not have received any Likes or Comments (e.g., users may feel inappropriate to like a post with sad news but also not motivated enough to write comments) are now likely to get Reactions (e.g., users can easily click the "sad" button). For such posts, these initial Reactions can then serve as the signal that may help attract subsequent engagement.[2]

Second, receiving Reactions can signal useful information to users regarding the content of a post, before users actually consume the content. This information is highly *accessible* to users, because the number and types of Reactions received by a post are presented in a visually outstanding manner below the post text (see the right panel in Figure 1 for an example user post that received some Reactions). It is also highly *diagnostic/indicative* of the post content, as it effectively "categorizes" the post into one or more of the five categories (i.e., love, haha, wow, sad, and angry). Accordingly, users are likely to use such information as input to decide which posts to read and engage, as indicated in the literature on information processing (Feldman and Lynch 1988). As a result, users can more easily discover posts of their interests to engage with, which can promote subsequent engagement activities, including Liking and Commenting. From this perspective, Reactions serve as a better signal than Likes and Comments. Compared with Reactions, Likes provide less specific information and are less diagnostic (Scissors et al., 2016); and Comments take longer time to read and process and are less accessible (Yang et al. 2019).

As a result of the signaling effect of Reactions, a user post that received some Reactions may attract more

[2] Note that we do not claim that only Reactions can serve as a signal for posts. Getting Likes or Comments may also serves as a signal and attracts subsequent engagement.

Likes and Comments, because other users want to join the conversation and add their own opinions. This is consistent with previous findings in the online review and online community literature, which show that existing participation can lead to more subsequent participation. For example, Dellarocas et al. (2010) examined the online reviews for motion pictures and found that people were more likely to write reviews for products that had already received many reviews. Ludford et al. (2004) found that "community activity begets activity" in online community contributions.

Finally, it is important to note that, although the substitution and reinforcement effects are directionally opposite, they are not mutually exclusive and may co-occur. For example, a particular user may choose to substitute Likes or Comments with Reactions based on his or her engagement goal; however, across users, Reactions may be perceived as a quality signal and attract more Likes and Comments. In this paper, our primary goal is to understand the aggregate, overall effect that Reactions may have on the use of Likes and Comments for individual posts. This is important because posts are the basic "units" of user-generated content on Facebook business pages. While different users may exhibit different engagement behaviors toward a post, it is the overall engagement (i.e., Likes, Comments, and Reactions) received by the post that indicates the impact of that post on various business-related outcomes, such as sales (Goh et al. 2013) and purchasing decisions (Rishika et al. 2013). Accordingly, we focus our analyses at the *post level*.[3]

2.5. Duration of Impact

An important question in the technology design and adoption literature (e.g., Bhattacherjee 2001; Kraut et al. 1998) is how long behavioral changes that are triggered by technologies last. The short-term usage pattern of a technology artifact can often be different from its long-term usage pattern. Hence, another interesting question is the duration of the impact of the Reactions feature.

Immediately after the feature change, Facebook users' adoption and use of the Reactions feature may be under the influence of the "novelty shock", i.e., the feature may be intensively used simply because it is new, and users are trying it out. The "novelty" effect is often considered in studies of new feature introduction (e.g., Lee and Benbasat 2003; Tung and Deng 2006). Statistics of Google Trend queries of the Reactions feature also support such "novelty shock", as shown in Figure 2. The number of Google searches for the term "Facebook Reaction" spiked immediately on 02/24/2016, i.e., the day when the Reactions feature was introduced, and subsided after a week. This indicates that many users were actively searching and learning about the new Reactions feature upon its release.

As time goes on, use of the Reactions feature may change as the novelty effect fades, and the long-term use of the feature largely depends on user satisfaction and perceived usefulness of the feature (Bhattacherjee 2001). If the Reactions feature is perceived to be useful and easy to use, then we can expect its use to continue or even increase. As a result, its impact on Likes and Comments is also likely to persist over time. However, if users are not satisfied with the Reactions feature, then the feature may lose its attraction. Its use will decrease, and the impact on Likes and Comments will not persist. Hence, another goal of our research is to *uncover and compare both the short-term and the long-term impact of the Reactions feature on Likes and Comments*.

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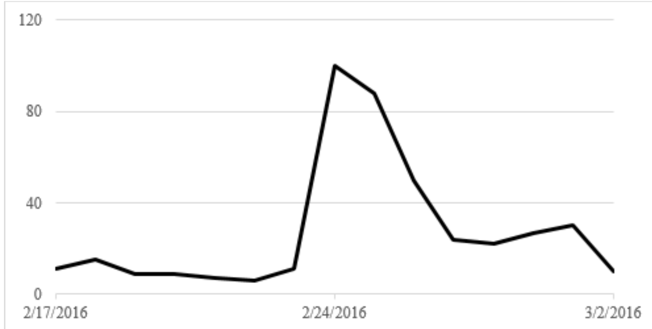
[3] As one of our empirical robustness checks, we tested the degree to which the substitution and reinforcement effects may coexist (Section 5.6). A more thorough examination of the exact substitution/reinforcement process requires comprehensive data at the *individual user* level with timestamp on each engagement activity, which we did not observe in our study.

Figure 2. Google Trend Query Result on "Facebook Reaction"



Note. Numbers on the Y-axis represent daily search volume relative to the highest daily search volume within the query period.

3. EMPIRICAL CONTEXT

3.1. Data

We collected data from the Facebook business pages of Fortune 500 companies in 6 consumer-oriented industries. We focused on Fortune 500 companies because they were early adopters of Facebook business pages, and their business pages had relatively high levels of traffic.[4] Among all industries, we chose the 6 industries that are consumer-oriented, i.e., Airlines, Commercial Banks, Consumer Products, Food and Drug Stores, General Merchandisers, and Specialty Retailers, because the topic of user-generated content is more relevant to consumer-oriented industries than to other (e.g., business-to-business) industries.

A total of 29 companies in these industries had active Facebook pages around the time of the feature change. We collected all user-generated posts on their pages, created 6 months before and 6 months after the introduction of the Reactions feature (i.e., 08/24/2015 to 08/24/2016). We constructed an unbalanced panel of 236,260 individual user posts across the 29 company pages. The company with the most user posts (33,990) was Walmart, and the company with the fewest user posts (441) was Conagra Brands. For each post, we collected its textual content, post type (status, video, or photo), time of creation, and the number of Likes and Comments it received. For posts created after the feature change, we also counted each type of Reactions it received. We only counted the number of Likes, Comments, or Reactions that were generated by Facebook users, rather than the focal companies. This is because (1) companies very rarely click Like or Reactions on user posts – fewer than 0.6% of user posts in our sample received any Likes or Reactions from the focal companies; and (2) companies make Comments on user posts primarily to respond to users' queries or complaints, which is outside the scope of our current work. It is worth noting that our main findings remained the same whether we counted company engagement or not.

We removed a subset of posts from our sample due to methodological considerations. We removed 12 user posts that were created in the 4 weeks before the feature change and continued to receive engagement after the feature change. We also removed 1,351 posts (i.e., fewer than 0.6% of all posts) that were created on users' own timelines with tags to the focal businesses (using the "@" sign, e.g., @WalMart), instead of being created on the business page. During the time of our data collection, user posts organically created

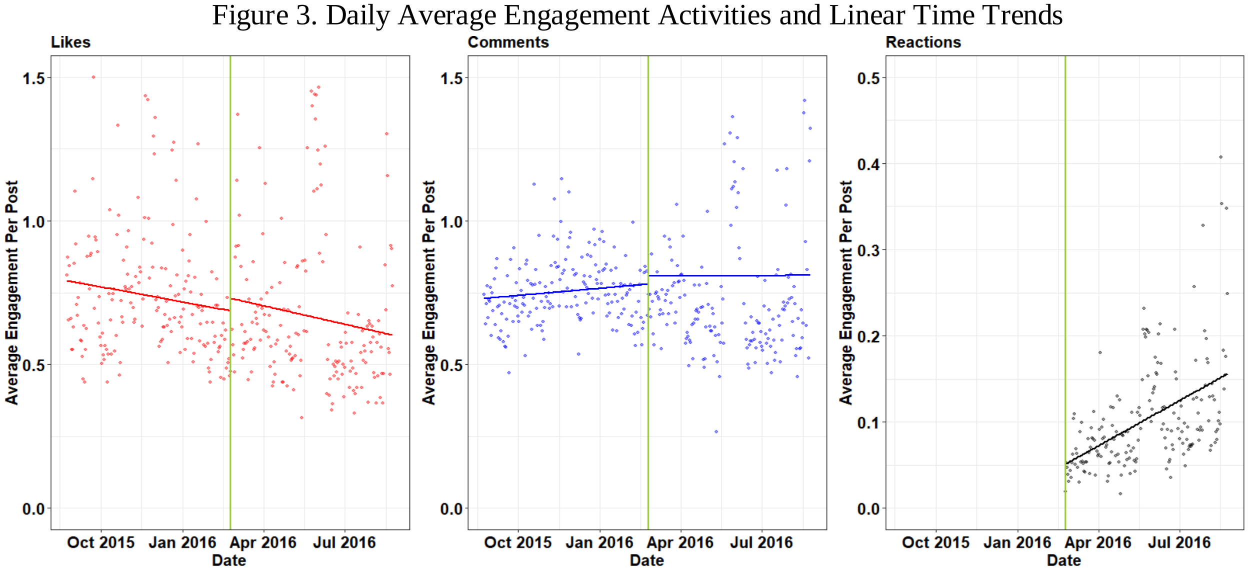
[4] The Facebook business pages of the companies in our sample had, on average, 5.32 million page likes and 5.14 million followers (data collected in October 2019). More than 75% (22 out of 29) companies in our sample had more than 1 million page likes and followers.

on business pages were visible *only* to visitors to the pages – they were displayed in the "Visitor Posts" section on the business pages in a reverse-chronological order.[5] In contrast, posts created on users' own timelines were also exposed to the users' personal social networks, and were subject to Facebook's proprietary algorithm that determines the visibility of posts to other users. Because we did not have access to users' personal social networks or the exact mechanism of Facebook's proprietary algorithm, we removed these 1,351 posts with tags to the focal businesses from our sample.

Besides Likes, Comments, and Reactions, Facebook also offers a "Share" feature, which we did not consider for several reasons. First, the Share feature is conceptually distinct from the other engagement features, because it propagates the content to users' personal Facebook friend networks (Malhotra et al. 2013). Users' motivations to share a post may be different from their motivations behind other types of engagement. Second, user posts on Facebook business pages has been rarely shared, with only 3% of the user posts in our sample received any Shares (compared to 35% receiving at least one Like and 36% receiving at least one Comment). Third, for user posts that did get shared, the subsequent engagement may come from the sharer's friend network, which is unobservable to us. Hence, we removed user posts that received any Shares from our sample.

As a visual illustration of our data, we plotted in Figure 3 the average number of Likes, Comments, and Reactions received by a user post on each day throughout our entire data collection period. The intensity of engagement activities fluctuated a lot from day to day. The plots also showed the linear time trends of each engagement activity, fitted separately before and after the feature change. We observed small upward jumps for both Likes and Comments around the feature change, as well as an upward trend for Reactions over time. Additional time trend plots (e.g., aggregating Likes and Comments) are included in Appendix D. We next analyze the impact of Reactions feature on different engagement activities more formally.

Figure 3. Daily Average Engagement Activities and Linear Time Trends



Note. The green vertical line marks the date of feature change. Linear time trends are fitted separately before and after the feature change for Likes and Comments.

[5] Authors obtained this information by opening an actual business page on Facebook and experimenting with different ways of creating and viewing user posts.

3.2. Methods

To estimate the impact of Reactions on overall engagement in the short term, we treated the introduction of the Reactions feature as a quasi-experiment (Angrist and Pischke 2008). Specifically, we used the introduction of the Reactions feature on 02/24/2016 as a cutoff point, and compared posts created immediately before the change with posts created immediately after the change to assess the overall impact of the feature change. The same methodology has been used in other studies to assess the impact of design and policy changes (e.g., Zhang and Zhu 2011; Cavusoglu et al. 2016; Kumar et al. 2017). When measuring overall engagement, we considered quantities of Likes, Comments, and Reactions both in a granular manner (i.e., their actual counts) and as high-level binary indicators (i.e., whether or not a post received *any* Likes, Comments, or Reactions).

After examining the impact on overall engagement, we analyzed the impact of Reactions on the use of Likes and Comments. Two methodological challenges arose in this set of analyses: (1) the effects of Reactions can potentially be heterogeneous depending on whether a post had received Reactions or not, and (2) receiving Reactions is not random, i.e., certain factors may affect a post's likelihood of getting not only Likes or Comments, but also Reactions. To address these challenges, we split the sample into posts that received Reactions and posts that did not receive any Reactions, and conducted sub-sample analyses using matching methods.

These empirical methods are appropriate for understanding the impact of Reactions for several reasons. First, the Reactions feature was enabled uniformly on the Facebook platform in the U.S. in a one-shot manner. Therefore, users had equal access to the Reactions feature, regardless of their geographic locations or devices. Second, although Facebook carefully planned the rollout of Reactions, there was no evidence suggesting that the rollout schedule was affected by user activities on the business pages in any way. In other words, the introduction of Reactions feature created a shock that was reasonably exogenous with respect to user engagement behaviors on business pages.

Following the short-term analyses, we then extended our sample to posts created 6 months before to 6 months after the feature change, to understand the long-term impact of Reactions. We report all the main analyses and results in the next section.

4. ANALYSES AND RESULTS

4.1. Short-Term Impact of Reactions on Overall Engagement

We first provide some descriptive statistics of engagement activities. The mean, standard deviation, bootstrapped 95% confidence interval of the mean, and median of different engagement activities both before and after the feature change are reported in Table 1. We also plot their distributions in Appendix C. We note that, in the short term after introduction of the Reactions feature, its usage was relatively low.

As model-free evidence regarding the impact of Reactions on engagement activities, we compared posts published 4 weeks before with those published 4 weeks after the introduction of Reactions feature along two dimensions: (1) average amount of engagement (of different types) received by each post and (2) fraction of posts that received any kind or amount (i.e., non-zero) of engagement. We summarize the comparison results in Table 2. There were significant increases in both the amount of total engagement (1.314 to 1.516, $p < 0.001$) and the percentage of posts that received any engagement (52.3% to 54.7%, $p < 0.001$). We also found significant differences for Likes and the sum of Likes and Comments, but not for

Comments.

Table 1. Descriptive Statistics of Likes, Comments, and Reactions per User Post (Short-Term)

	Before Feature Change (4 weeks, N = 14,974)				After Feature Change (4 weeks, N = 14,009)			
	Mean	SD	95% CI	Median	Mean	SD	95% CI	Median
Likes	0.597	1.811	[0.569, 0.626]	0	0.727	1.881	[0.695, 0.756]	0
Comments	0.717	1.625	[0.690, 0.742]	0	0.731	1.525	[0.706, 0.757]	0
Reactions	NA	NA	NA	NA	0.058	0.381	[0.051, 0.064]	0

Note. Because the empirical distributions of engagement activities are highly skewed, we estimate the 95% confidence interval of the mean with bootstrapping (1,000 replications).

Table 2. Model-Free Comparisons of Engagement Before and After Feature Change (Short-Term)

	Engagement Type	Before	After	T-Test	MANOVA Test
Average amount of engagement per post	Likes	0.597	0.727	***	F.stat = 117.88, $p < 0.001$
	Comments	0.717	0.731	n.s.	
	Likes+Comments	1.314	1.458	***	
	Total Engagement	1.314	1.516	***	
Fraction of posts that received engagement	Likes	0.308	0.333	***	F.stat = 32.34, $p < 0.001$
	Comments	0.358	0.355	n.s.	
	Likes+Comments	0.523	0.540	**	
	Total Engagement	0.523	0.547	***	

Note. Before feature change, total Engagement includes Likes and Comments. After feature change, total engagement includes Likes, Comments, and Reactions. T-tests are used to show whether the differences before and after the change for each engagement type are statistically significant. A MANOVA test is used to show whether the joint distribution of different types of engagement (i.e., Likes, Comments, Likes+Comments, and Total Engagement) changes significantly. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, n.s. not significant.

Next, we estimated the following regression specification to examine the impact of Reactions on engagement:

$$y_{ij} = \beta_0 + \beta_1\, After_{ij} + \beta_2\, Day_{ij} + \beta_3\, After_{ij} \times Day_{ij} + \boldsymbol{\Gamma}\, Company_j + \boldsymbol{\Phi}\, Type_{ij} + \varepsilon_{ij}$$

We considered two different dependent variables, y_{ij}: (1) the count of engagement received by post i on company page j; and (2) a binary variable indicating whether post i on company page j received any engagement. Note that, when measuring engagement, we considered both the sum of Likes and Comments (i.e., features available both before and after the introduction of Reactions) as well as the sum of Likes, Comments, and Reactions.

For independent variables, $After_{ij}$ is a dummy indicator of whether the post was created before or after the change; Day_{ij} represents the date on which the user post was created relative to 02/24/2016. For example, a post created on 02/23/2016 has a relative date of -1, whereas a post created on 02/25/2016 has a relative date of 1. Posts created exactly on 02/24/2016 were not included in these analyses, because we did not have information about the exact time when the feature change took place. We also included the interaction term $After_{ij} \times Day_{ij}$ to control for time trends both before and after the change. We included company and post type fixed effects, as $Company_j$ and $Type_{ij}$, to account for unobserved heterogeneity. The coefficient of interest is β_1 (i.e., coefficient on dummy variable $After_{ij}$), which captures the impact of the feature change on engagement, after controlling for time trends and other factors. The specification is estimated as a Poisson regression for the first dependent variable (Model 1), and a logistic regression for the second dependent variable (Model 2). The regression results are reported in Table 3.

Table 3. Short-Term Regression Estimation Results (N = 28,983)

	Model 1	Model 2
After	**0.134*** (0.040)**	**0.136** (0.051)**
Day	-0.003^{+} (0.002)	-0.004* (0.002)
After × Day	0.001 (0.003)	-0.0004 (0.002)
Company fixed effects	Included	Included
Type fixed effects	Included	Included
Constant	-0.393*** (0.091)	-0.890*** (0.114)
Pseudo R^2	0.075	0.040

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard error in parentheses. Dependent variable is the number of Likes and Comments a post received (Model 1) and whether a post received any Likes or Comments (Model 2). Model 1 is estimated as a Poisson regression. Model 2 is estimated as a logistic regression.

Our results showed a significant positive effect of the Reactions feature on both the amount of engagement as well as the likelihood of receiving any engagement.[6] After the introduction of the Reactions feature, an average user post received more Likes and Comments than before the feature change ($\beta_1 = 0.134$, $p < 0.001$), and it was also more likely to receive any Likes and Comments than before ($\beta_1 = 0.136$, $p < 0.001$). Table 3 also reports the McFadden Pseudo R^2 (McFadden 1977), which is a commonly used measure of goodness-of-fit for generalized linear regressions. It measures the change in log-likelihood of a model with all independent variables over an intercept-only model. Having a larger Pseudo R^2 indicates better model fit.

4.2. Short-Term Sub-Sample Analyses

The above analyses provided strong evidence of a positive effect of Reactions on overall engagement for an average user post. However, it is important to note that not all user posts that were created after the feature change received Reactions, and this positive effect should not be interpreted as a reinforcement effect. If Reactions truly reinforced Likes or Comments, then we should expect posts that received Reactions to have more Likes or Comments than what they would have received before the feature change. In order to understand Reactions' impact on existing engagement features, i.e., Likes and Comments, we partitioned the sample of user posts after feature change into two non-overlapping subsamples: (1) 591 posts that received at least one Reaction and (2) 13,418 posts that did not receive any Reactions. We then examined the effects of Reactions on Likes and Comments for each of the subsamples separately.

Directly comparing posts that received Reactions with posts before the feature change suffers from the endogeneity issue, because key characteristics of a post, such as its content quality or popularity, may affect both the number of Likes/Comments and the number of Reactions it receives. Therefore, we used propensity score matching (Rosenbaum and Rubin 1983) to construct a proper comparison group. Each post that received Reactions was matched with the nearest counterfactual among pre-change posts, based on 7 post-level observables described as follows:

- The company that owns the page where the post appeared;
- Post type, one of status, video, or photo;
- Post length, measured as word count;

[6] Not surprisingly, if we include Reactions as part of overall engagement after the feature change, the positive effects of Reactions would become even stronger.

- Post sentiment variables: (1) percentage of positive words and (2) percentage of negative words, calculated using the Linguistic Inquiry and Word Count (LIWC) software (Pennebaker et al. 2007);
- Post contextual variables: (1) the number of other user-generated posts created on the same page 24 hours before and 24 hours after the creation of the focal post and (2) the number of company-generated posts created on the same page 24 hours before and 24 hours after the creation of the focal post. We used these two variables to measure the number of other posts on the page that might compete for users' attention with the focal post.

The propensity score was estimated with a logistic regression and the matching was done using the nearest-neighbor approach, which is a standard approach in propensity score matching (Becker and Ichino 2002; Dehejia 2005). The 591 posts that received Reactions were matched with 591 pre-change counterfactual posts. We then estimated the effect by comparing the two matched samples with a t-test.

We found that, while a post in the pre-change matched sample received an average of 1.080 Likes, a post with Reactions received an average of 2.792 Likes ($t = 6.82$, $p < 0.001$), indicating a strongly positive effect. We also found a positive effect on the number of Comments. While a post in the pre-change matched sample received an average of 0.951 Comments, a post with Reactions received an average of 1.892 Comments ($t = 6.56$, $p < 0.001$). Therefore, posts that received at least one Reaction received *more* Likes and *more* Comments than they would have before the feature change. These findings suggested a reinforcement effect, rather than a substitution effect, for both Likes and Comments.

We also calculated the effect sizes of the above comparisons with Cohen's *d*, which measures the standardized difference between means (Cohen 2013). The impact of Reactions on Likes had a Cohen's *d* of 0.40, and the impact of Reactions on Comments had a Cohen's *d* of 0.38. Following Cohen (2013), these effect sizes were relatively small.[7] However, we note that the percentage increases of Likes and Comments for a post with Reactions were 158.5% and 98.9% respectively, which were substantial. Given the large volume of user posts on Facebook business pages, relatively small engagement increase *per post* can amass to sizable impact on the business pages as a whole.

To assess the quality of our propensity score matching process, we estimated the Rosenbaum Bound (Rosenbaum 2002) as a measure of the sensitivity of our findings with respect to unobserved selection variables. The Rosenbaum Bound of a treatment effect estimation has a critical value, which indicates how likely the estimated effects can be invalidated by unobserved variables that affect the odds of selection into the treatment group. For the analysis of Likes, the Rosenbaum Bound is 3.0, suggesting that unobserved variables would need to alter the odds of getting Reactions by 200% in order to invalidate the effect. For the analysis of Comments, the Rosenbaum Bound is 3.6, suggesting that unobserved variables would have to alter the odds of getting Reactions by 260% in order to invalidate the effect. Both values indicate our findings are highly unlikely to be nullified by unobserved selection variables. In addition, we plotted the distributions of propensity scores before and after matching in Figure 4. Propensity score distributions of control posts and treatment posts become much more similar after matching (indicated by much larger overlaps in distributions), which again indicated good matching quality.

As another verification of our propensity score matching quality, we conducted an experiment on Amazon Mechanical Turk, by randomly sampling 10 pairs of matched posts and asked Turkers to indicate their

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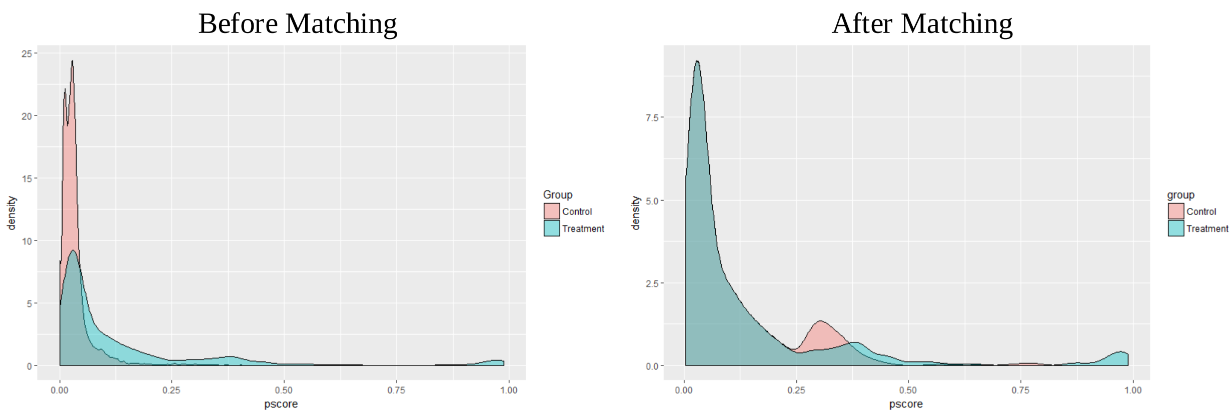
[7] Following Cohen (2013), we considered $0.2 \leq d < 0.5$ as a small effect size, $0.5 \leq d < 0.8$ as a medium effect size, and $d \geq 0.8$ as a large effect size.

likelihood of using the Reactions feature to engage with the posts. We found no significant differences in the likelihood of receiving Reactions between the matched posts ($Mean_{before}$ = 45.30%, $Mean_{after}$ = 45.96%, p = 0.821). The experiment design and more detailed results are included in Appendix A.

We repeated the analyses with an alternative matching approach, known as the Coarsened Exact Matching (Iacus et al. 2012). Instead of matching treatment units with control units using propensity scores, this approach seeks *exact* matches between treatment and control units, based on discretized ("coarsened") matching variables. It has been shown to outperform propensity score matching in producing a more balanced matched sample (Iacus et al. 2012; King and Nielsen 2016). Using this method, we matched 433 (out of 591) posts that received Reactions with 7,809 pre-change counterfactual posts. The matched sample achieved good balance on all matching covariates. The percentage balance improvement is positive for every matching covariate ranging from 18% to 100%, and the overall balance improvement is 99%.[8]

Figure 4. Distribution of Propensity Scores Before and After Matching for Short-Term Analysis



With the new sample, we obtained qualitatively similar results for both Likes and Comments. Comparing the two matched samples, posts with Reactions received significantly more Likes ($Mean_{before}$ = 0.554, $Mean_{after}$ = 2.217, $p < 0.001$, Cohen's d = 0.84, percentage change 300.2%), and more Comments ($Mean_{before}$ = 0.819, $Mean_{after}$ = 2.166, $p < 0.001$, Cohen's d = 0.78, percentage change 164.5%). The sizes of positive effects were medium to large (Cohen 2013). These results further showed the robustness of our findings.

We performed another robustness test by looking into the complementarity of Reactions and Comments. Technically speaking, the Reactions and Comments features are not mutually exclusive. For a given post, while a user *cannot* click both Reactions and Like buttons, he/she *can* both click a Reactions button and leave a Comment. In other words, the observed increase in the number of Comments for posts with Reactions might be because many users used the Reactions feature *and* the Comment feature on the same posts. To rule out this possibility, we re-ran the propensity score matching analysis, by excluding all the Comments that were made by users who had also clicked the Reactions on the same posts. We obtained

[8] Having a more balanced sample after matching means that the treatment and control units are more similar on the matching covariates. For a particular matching covariate, the percentage balance improvement statistic indicates how much more balanced the sample has become compared to the original sample before matching. Denoting the mean absolute difference between treatment and control units as a in the original sample and as b in the matched sample, the percentage balance improvement is calculated as $100(a-b)/a$ %. Therefore, 100% balance improvement means that the treatment and control units in the matched sample have equal means on a particular covariate. Finally, the overall percentage balance improvement indicates the balance improvement across all matching covariates.

similar findings. Posts that received Reactions still received more Comments than pre-change matched sample ($Mean_{before}$ = 0.951, $Mean_{after}$ = 1.736, $p < 0.001$, Cohen's $d = 0.33$, percentage change 82.5%). This suggests that the increases in Comments were not primarily driven by the simultaneous use of both Reactions and Comments by the same users.

What about the posts that did not receive any Reactions? In another set of analyses, we compared the 13,418 posts that did not receive any Reactions with the matched pre-change posts. We used coarsened exact matching instead of propensity score matching in this case, because the latter failed to reach a reasonable Rosenbaum sensitivity bound, indicating unstable matching results. We were able to match 10,627 of 13,418 posts with 11,740 pre-change counterfactual posts. The percentage balance improvement was positive for every matching covariate, ranging from 58% to 100%, and the overall balance improvement is 95%. We found that, while a post in the pre-change matched sample received an average of 0.558 Likes, a post without any Reaction received an average of 0.488 Likes ($t = 3.57$, $p < 0.01$, Cohen's $d = 0.05$, percentage change −12.5%), indicating a negative effect. We also found a negative effect on Comments. While a post in the pre-change matched sample received an average of 0.758 Comments, a post without any Reaction received an average of 0.705 Comments ($t = 2.52$, $p < 0.01$, Cohen's $d = 0.03$, percentage change −7.0%). While these effects were statistically significant, their sizes were very small.

Overall, our sub-sample analyses suggest that the introduction of the Reactions feature had heterogeneous effects on the two sub-samples of user posts. We found strong evidence that posts receiving Reactions ended up also receiving more Likes and more Comments than what they would have received before the feature change. In contrast, posts that were created after the change yet did not receive any Reactions ended up receiving fewer Likes and fewer Comments than they would have received before the feature change, although the effect sizes were small. Thus, the introduction of the Reactions feature reinforced engagement for user posts that had received Reactions and had a weak cannibalization effect on engagement for the posts that did not receive any Reactions.

It is important to note that the heterogeneous effects obtained from sub-sample analyses do not contradict the positive effects of Reactions on the overall engagement we showed previously. The overall increase of Likes and Comments for an average user post was driven primarily by the strong positive effect on posts that received Reactions. Meanwhile, the negative effect on posts that did not receive Reactions was not strong enough to offset the aforementioned positive effect.

4.3. Analyses of Impact Duration

So far, we have only considered the short-term effects of Reactions on engagement. In this section, we expanded the time window of our analyses to include all posts created 6 months before and 6 months after the feature change, in order to analyze the long-term effects. Informed by our short-term findings, for all analyses in this section, we examined posts that received vs. did not receive Reactions separately, to account for the heterogeneity in the long-term effects.

Table 4 shows the descriptive statistics of the Likes, Comments, and Reactions received by the user posts and their distribution plots are included in Appendix C. An average post received more Reactions in the 6 months after the feature change (0.114 Reactions per post) than in the 4 weeks after the change (0.058 Reactions per post). The fraction of posts that received at least one Reaction were also higher in the 6-

month window (7,529 out of 98,321, or 7.66%) than in the 4 weeks window (591 out of 14,009, or 4.22%).[9] This provided descriptive evidence that the use of the Reactions feature persisted and continued to increase in the long term.

Table 4. Descriptive Statistics of Likes, Comments, and Reactions per User Post (Long-Term)

	Before Feature Change (6 months, N = 128,398)				After Feature Change (6 months, N = 98,321)			
	Mean	SD	95% CI	Median	Mean	SD	95% CI	Median
Likes	0.851	2.276	[0.838, 0.863]	0	0.760	2.040	[0.747, 0.772]	0
Comments	0.763	1.622	[0.753, 0.771]	0	0.795	1.777	[0.784, 0.807]	0
Reactions	NA	NA	NA	NA	0.114	0.526	[0.110, 0.117]	0

Note. Because the empirical distributions of engagement activities are highly skewed, we estimate the 95% confidence interval of the mean with bootstrapping (1,000 replications).

Next, we conducted matching analyses to estimate the long-term effects. The results from both propensity score matching and coarsened exact matching are summarized in Table 5. For posts that received at least one Reaction, we found significant positive effects on both Likes and Comments. The effect sizes are small to medium under propensity score matching and large under coarsened exact matching. User posts that received Reactions ended up receiving more Likes and Comments than what they would have received before the feature change. This is consistent with our findings from the short-term analyses, indicating that the impact of the Reactions feature persisted in the long term.

For posts that did not receive any Reactions, we instead found significant negative effects on both Likes and Comments, though the effect sizes were very small. A post created after the change that did not receive any Reactions ended up receiving fewer Likes and fewer Comments than it would have before the change. Again, the long-term effects on Likes and Comments are consistent with the short-term effects, suggesting a persistent impact of the Reactions feature over time.

Table 5. Long-Term Matching Analyses Results

		Posts with Reactions		Posts without Reactions	
		Likes	Comments	Likes	Comments
Propensity Score Matching	Average before change	1.443	0.942	0.813	0.717
	Average after change	2.642	2.394	0.603	0.663
	t-test significance	***	***	***	***
	Cohen's *d*	0.28	0.52	0.11	0.04
	Percentage change	83.1%	154.1%	-25.8%	-7.5%
Coarsened Exact Matching	Average before change	0.759	0.778	0.758	0.754
	Average after change	2.717	2.577	0.556	0.680
	t-test significance	***	***	***	***
	Cohen's *d*	0.79	0.99	0.11	0.05
	Percentage change	258.0%	231.2%	-26.6%	-9.8%

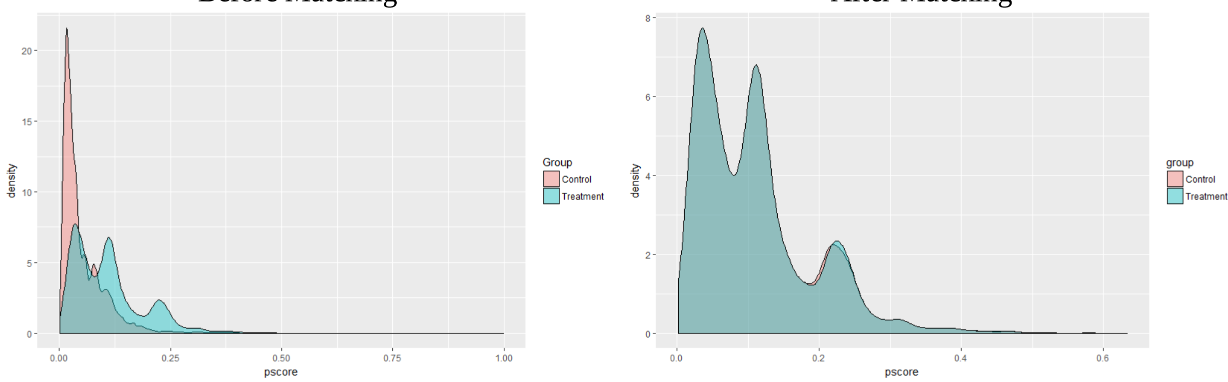
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

[9] A MANOVA test shows significant differences in the joint distributions of average Reactions per post and fraction of posts with at least one Reactions in the short-term versus in the long-term (F.stat = 109.60, $p < 0.001$).

In addition, we calculated the Rosenbaum sensitivity bounds of the propensity score matching processes. For the matching process regarding posts with Reactions, the critical Rosenbaum bound is 2.5 for Likes and 3.2 for Comments. We also plotted the distribution of propensity scores before and after matching in Figure 5. Propensity score distributions of control posts and treatment posts become almost identical after matching, again showing good matching quality. For the matching process regarding posts without Reactions, the critical Rosenbaum bound is 1.2 for Likes and 1.1 for Comments. Under coarsened exact matching, the overall percentage balance improvement reached 99% for both sets of matching, indicating good matching quality. While the critical Rosenbaum bounds for posts without Reactions are relatively low, the associated findings are consistent with those obtained by coarsened exact matching, indicating the overall robustness of our findings.

Figure 5. Distribution of Propensity Scores Before and After Matching for Long-Term Analysis

Before Matching | After Matching



We repeated the above analyses using regression methods and obtained qualitatively similar results. We controlled for the same 7 post-level characteristics that were used for matching and used the following model specification:

$$y_{ij} = \beta_0 + \beta_1\, After_{ij} + \beta_2\, Length_{ij} + \beta_3\, Positive_{ij} + \beta_4\, Negative_{ij} + \beta_5\, UGC_{ij} + \beta_6\, MGC_{ij}$$
$$+ \boldsymbol{\Psi}\, Month_{ij} + \boldsymbol{\Gamma}\, Company_j + \boldsymbol{\Phi}\, Type_{ij} + \varepsilon_{ij}$$

Here, $Length_{ij}$ represents the word count of the post. $Positive_{ij}$ and $Negative_{ij}$ represent the percentage of positive/negative words in the post. UGC_{ij} and MGC_{ij} represent the number of other user-generated/company-generated posts created within 24 hours before and 24 hours after the creation of the focal post. $Company_j$ and $Type_{ij}$ represent company and post type fixed effects. In addition, we also included month fixed effects, represented by $Month_{ij}$, to control for unobserved time heterogeneity at the month level. Similar to our short-term analyses, β_1 captures the impact of Reactions on the dependent variable. A similar approach has been adopted by Cavusoglu et al. (2016) in understanding the long-term impact of a particular policy change on Facebook. The specification was estimated as a Poisson regression with robust standard errors. The regression results are reported in Table 6.

For posts that received at least one Reaction, we found a significant positive effect on Likes ($\beta_1 = 0.192$, $p < 0.001$), and a significant positive effect on Comments ($\beta_1 = 1.083$, $p < 0.001$). For posts that did not receive any Reactions, we again found a significant negative effect on Likes ($\beta_1 = -0.746$, $p < 0.001$), and a significant negative effect on Comments ($\beta_1 = -0.180$, $p < 0.001$).

Table 6. Long-Term Effects Poisson Regression Estimation Results

	DV = Likes		**DV = Comments**	
	Posts with Reactions	Posts without Reactions	Posts with Reactions	Posts without Reactions
After	**0.192*** (0.045)**	**-0.746*** (0.025)**	**1.083*** (0.031)**	**-0.180*** (0.023)**
Length	0.0003** (0.0001)	0.0003*** (0.0000)	0.0004*** (0.0001)	0.0004*** (0.0001)
Positive	0.009*** (0.001)	0.007*** (0.001)	-0.030*** (0.001)	-0.033*** (0.001)
Negative	0.012*** (0.001)	0.015*** (0.001)	0.006*** (0.001)	0.005*** (0.001)
UGC	0.0004*** (0.0000)	0.001*** (0.0000)	-0.0002*** (0.0000)	-0.0001*** (0.0000)
MGC	-0.062*** (0.006)	-0.067*** (0.005)	-0.001 (0.005)	-0.003 (0.004)
Month fixed effects	Included	Included	Included	Included
Company fixed effects	Included	Included	Included	Included
Type fixed effects	Included	Included	Included	Included
Constant	0.027 (0.057)	0.004 (0.050)	-1.138*** (0.061)	-1.363*** (0.054)
N	135,927	219,190	135,927	219,190
Pseudo R^2	0.126	0.098	0.084	0.060

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors included in parentheses.

5. ADDITIONAL ROBUSTNESS CHECKS AND ANALYSES

The above analyses have offered ample evidence that getting Reactions led a user post to receive more Likes and Comments than it would have received prior to the feature change, and such reinforcement effects manifested both in the short term and in the long term. In this section, we conducted a comprehensive set of robustness checks to further validate our main findings and also provide some additional insights.

5.1. Robustness Checks for the Impact of Reactions on Overall Engagement

We concluded in Section 4.1 that the Reactions feature had a positive effect on overall engagement. Here we conducted multiple robustness checks to verify this overall effect. First, for analysis on the number of Likes and Comments, we estimated two alternative model specifications: a negative binomial regression and a linear regression with log-transformed dependent variables. For analysis on whether a post received any Likes and Comments, we estimated an alternative OLS regression. Second, we repeated the analyses using an alternative time window of 3 weeks, instead of 4 weeks, before and after the feature change.[10] Third, we conducted additional falsification tests, by artificially moving the feature change date to either 4 weeks earlier than 02/24/2016 or 4 weeks later, and estimated the "pseudo" effects for each scenario. Our results remained qualitatively consistent in the first two robustness checks. For the third robust check, the estimated "pseudo" effects were all insignificant, indicating that our positive effects cannot merely be attributed to general time trends. Results of the above checks are included in Tables 7 and 8.

[10] We have also examined the alternative time windows of 2 weeks and 1 week. The sample sizes were relatively small, and the effects of Reactions on engagement were statistically insignificant.

Table 7. Robustness Checks for the Effects of Reactions on Amount of Engagement

	(1)	(2)	(3)	(4)	(5)
After	**0.078***	**0.054*****	**0.169****	**-0.045**	**0.005**
	(0.039)	**(0.016)**	**(0.025)**	**(0.042)**	**(0.049)**
Day	-0.003	-0.001+	-0.007***	-0.003+	-0.004+
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
After × Day	0.002	-0.0003	0.003+	0.001	0.014***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)
Company fixed effects	Included	Included	Included	Included	Included
Type fixed effects	Included	Included	Included	Included	Included
Constant	-0.447***	0.281***	-0.442***	-0.066	-0.087
	(0.091)	(0.033)	(0.058)	(0.102)	(0.105)
N	28,983	28,983	22,127	31,983	26,520
Pseudo R^2	0.094	0.090	0.077	0.070	0.078

$^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Models are estimated as Poisson Regressions. Robust standard errors in parentheses. Column definitions: (1) negative binomial regression; (2) OLS with log transformed DV; (3) alternative time window, 3 weeks; (4) pseudo effect on 01/27/2016; (5) pseudo effect on 03/23/2016. For model (2), the regular R^2 is reported instead of the McFadden's Pseudo R^2.

Table 8. Robustness Checks for the Effects of Reactions on the Likelihood of Receiving Engagement

	(1)	(2)	(3)	(4)
After	**0.034****	**0.094**	**-0.038**	**0.012**
	(0.012)	**(0.059)**	**(0.048)**	**(0.053)**
Day	-0.001*	-0.000	0.001	-0.002
	(0.001)	(0.003)	(0.002)	(0.003)
After × Day	-0.0002	-0.004	-0.005+	0.005
	(0.001)	(0.005)	(0.003)	(0.003)
Company fixed effects	Included	Included	Included	Included
Type fixed effects	Included	Included	Included	Included
Constant	0.296***	-0.879***	-0.515***	-0.480***
	(0.026)	(0.126)	(0.109)	(0.131)
N	28,983	22,127	31,983	26,520
Pseudo R^2	0.051	0.044	0.033	0.047

$^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Models are estimated as Logistic Regressions. Robust standard errors in parentheses. Column definitions: (1) OLS regression; (2) alternative time window, 3 weeks; (3) pseudo effect on 01/27/2015; (4) pseudo effect on 03/23/2016. For model (1), the regular R^2 is reported instead of the McFadden's Pseudo R^2.

5.2. Robustness Checks for Short-Term Sub-Sample Analyses

In our short-term analyses, we relied on matching methods to establish the heterogeneous effects of the Reactions feature on Likes and Comments. We replicated the sub-sample analyses with regression-based approaches. Specifically, we repeated the analyses by controlling for all 7 post-level characteristics, instead of matching on them, with the following regression specification:

$$y_{ij} = \beta_0 + \beta_1\, After_{ij} + \beta_2\, Length_{ij} + \beta_3\, Positive_{ij} + \beta_4\, Negative_{ij} + \beta_5\, UGC_{ij} + \beta_6\, MGC_{ij}$$
$$+ \boldsymbol{\Gamma}\, Company_j + \boldsymbol{\Phi}\, Type_{ij} + \varepsilon_{ij}$$

The specification was estimated as a Poisson regression. The results were qualitatively consistent with matching results, as summarized in Table 9.

Table 9. Sub-Sample Poisson Regression Estimation Results

	DV = Likes		DV = Comments	
	Posts with Reactions	Posts without Reactions	Posts with Reactions	Posts without Reactions
After	**1.030*** (0.095)**	**-0.030 (0.030)**	**0.819*** (0.069)**	**-0.072** (0.026)**
Length	0.001*** (0.0001)	0.001*** (0.0001)	0.001*** (0.0001)	0.0004*** (0.0001)
Positive	0.008*** (0.002)	0.004* (0.002)	-0.040*** (0.004)	-0.038*** (0.003)
Negative	0.008^{+} (0.004)	0.013*** (0.002)	0.014* (0.007)	0.009* (0.004)
UGC	0.001* (0.001)	0.002*** (0.0002)	-0.003*** (0.001)	-0.003*** (0.0003)
MGC	0.052^{+} (0.028)	-0.009 (0.016)	0.013 (0.021)	0.019 (0.014)
Company fixed effects	Included	Included	Included	Included
Type fixed effects	Included	Included	Included	Included
Constant	-1.143*** (0.179)	-0.941*** (0.110)	-1.142*** (0.214)	-1.290*** (0.147)
N	15,565	28,392	15,565	28,392
Pseudo R^2	0.171	0.118	0.081	0.059

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors included in parentheses.

5.3. Checking for "Novelty Shock" and "Anticipation Effect"

We took the sample of user posts created 4 weeks before and 4 weeks after the feature change, and checked the effects of the Reactions feature against two possible confounding scenarios: (1) the existence of a "novelty shock", that is, the observed effects were purely driven by the extensive use of the Reactions feature immediately after its introduction simply because it was new; and (2) the existence of an "anticipation effect", that is, users' engagement behaviors might be structurally different as the rollout of Reactions became close, in anticipation of the feature change. Either confounding scenarios, if true, undermines the validity of our results.

To check against the "novelty shock", we re-estimated the sub-sample regression (Section 5.2) using all 4 weeks before the feature change, but only the 3rd and 4th week after the change (i.e., removing the first two weeks immediately following the change). The results are reported in Table 10. We continued to find significant positive effects on Likes and Comments for posts that received Reactions, as well as significant negative effects on Likes and Comments for posts that did not receive Reactions. Therefore, our findings cannot be simply attributed to a short-term "novelty shock."

Next, to check against the "anticipation effect", we repeated the above analyses using the 3rd and 4th week both before and after the feature change (i.e., removing the 2 weeks immediately before the feature change and the 2 weeks immediately after the feature change). Our main results again remained qualitatively similar, ruling out the "anticipation effect". The results are reported in Table 11.

Table 10. Sub-Sample Poisson Regression Results, Removing First 2 Weeks after Feature Change

	DV = Likes		**DV = Comments**	
	Posts with Reactions	Posts without Reactions	Posts with Reactions	Posts without Reactions
After	**0.960*****	**-0.161*****	**0.785*****	**-0.072***
	(0.130)	**(0.040)**	**(0.089)**	**(0.032)**
Length	0.001***	0.001***	0.001***	0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Positive	0.007**	0.007***	-0.041***	-0.041***
	(0.003)	(0.002)	(0.004)	(0.003)
Negative	0.012***	0.016***	0.014*	0.013*
	(0.004)	(0.003)	(0.007)	(0.006)
UGC	-0.001	0.001	-0.003***	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
MGC	0.059*	-0.005	0.024	0.019
	(0.029)	(0.019)	(0.022)	(0.016)
Company fixed effects	Included	Included	Included	Included
Type fixed effects	Included	Included	Included	Included
Constant	-1.012***	-1.089***	-1.212***	-1.364***
	(0.217)	(0.183)	(0.228)	(0.197)
N	15,264	21,614	15,264	21,614
Pseudo R^2	0.160	0.111	0.075	0.062

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors included in parentheses.

Table 11. Sub-Sample Poisson Regression Results, Removing Immediate 4 Weeks around Feature Change

	DV = Likes		**DV = Comments**	
	Posts with Reactions	Posts without Reactions	Posts with Reactions	Posts without Reactions
After	**0.947*****	**-0.208*****	**0.822*****	**-0.051**
	(0.145)	**(0.047)**	**(0.097)**	**(0.038)**
Length	0.001***	0.0004***	0.001***	0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Positive	0.008*	0.007**	-0.033***	-0.036***
	(0.003)	(0.003)	(0.006)	(0.004)
Negative	0.013**	0.016***	0.017^{+}	0.014^{+}
	(0.004)	(0.003)	(0.010)	(0.007)
UGC	-0.0001	0.003*	-0.003*	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)
MGC	0.075^{+}	-0.015	0.011	0.010
	(0.040)	(0.024)	(0.029)	(0.018)
Company fixed effects	Included	Included	Included	Included
Type fixed effects	Included	Included	Included	Included
Constant	-1.003***	-1.078***	-1.113***	-1.361***
	(0.296)	(0.224)	(0.303)	(0.240)
N	8,123	14,473	8,123	14,473
Pseudo R^2	0.191	0.114	0.073	0.056

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors included in parentheses.

5.4. Accounting for the Interplay between Likes and Comments

In our main analyses, we have treated the number of Likes and Comments as independent measures of engagement. However, the two can be correlated with each other, because engaging user posts tend to attract both Likes and Comments. To account for such correlation, we re-ran the analyses by including the number of Likes as an independent variable into regressions on Comments, and vice versa. This was done for both short-term and long-term analyses, and the results are reported in Tables 12 and 13. Our results remained largely unchanged. Although there were two instances where the coefficient of *After* became statistically insignificant, the direction of the effects remained the same. Meanwhile, the coefficients on both Likes and Comments were positive and significant, indicating that there was indeed a positive association between the two.

Table 12. Short-Term Poisson Regression Results, Accounting for Correlation between Likes and Comments

	DV = Likes		**DV = Comments**	
	Posts with Reactions	Posts without Reactions	Posts with Reactions	Posts without Reactions
After	**0.945*** (0.094)**	**-0.014 (0.030)**	**0.729*** (0.071)**	**-0.063* (0.026)**
Length	0.001*** (0.0001)	0.0004*** (0.0001)	0.001*** (0.0001)	0.0004*** (0.0001)
Positive	0.010*** (0.002)	0.006** (0.002)	-0.042*** (0.004)	-0.038*** (0.003)
Negative	0.005 (0.005)	0.012*** (0.002)	0.014* (0.007)	0.009* (0.004)
UGC	0.002*** (0.001)	0.002*** (0.0002)	-0.003*** (0.001)	-0.003*** (0.0003)
MGC	0.051^{+} (0.027)	-0.013 (0.015)	0.007 (0.022)	0.022 (0.014)
Company fixed effects	Included	Included	Included	Included
Type fixed effects	Included	Included	Included	Included
Constant	-1.183*** (0.177)	-0.969*** (0.110)	-1.151*** (0.212)	-1.307*** (0.146)
Likes	-	-	0.046*** (0.006)	0.057*** (0.009)
Comments	0.077*** (0.009)	0.083*** (0.009)	-	-
N	15,264	21,614	15,264	21,614
Pseudo R^2	0.187	0.132	0.091	0.069

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors included in parentheses.

5.5. Quantile Regressions

In this sub-section, we repeated our short-term and long-term analyses with quantile regressions. Compared with the generalized OLS method (e.g., the Poisson regressions we used in the main analyses), which estimates the conditional *mean* of dependent variables given values of independent variables, the quantile regression method estimates the conditional *quantiles* of dependent variables given independent variables. Quantile regression has two major advantages over OLS, both of which are relevant in our context. First, it is less susceptible to outliers in dependent variables, resulting in more robust coefficient estimates, even when a small number of posts received a disproportionally high amount of engagement (Gao et al. 2015). Second, while Poisson regression estimates the *average* effect among all user posts, the quantile regression allows us to examine whether the effect stays robust across user posts with different levels of "popularity", as indicated by the amount engagement they received (Oestreicher-Singer and Sundararajan 2012). If the estimated effects across multiple quantiles are consistent, it will provide additional validation of our findings and a more comprehensive view of the effect.

Table 13. Long-Term Poisson Regression Results, Accounting for Correlation between Likes and Comments

	DV = Likes		**DV = Comments**	
	Posts with Reactions	Posts without Reactions	Posts with Reactions	Posts without Reactions
After	**0.052**	**-0.716*****	**1.066*****	**-0.142*****
	(0.045)	**(0.026)**	**(0.031)**	**(0.022)**
Length	0.0003***	0.0003***	0.0004***	0.0004***
	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Positive	0.010***	0.009***	-0.032***	-0.035***
	(0.001)	(0.001)	(0.002)	(0.001)
Negative	0.011***	0.014***	0.006***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
UGC	0.0004***	0.001***	-0.0002***	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
MGC	-0.059***	-0.066***	0.002	0.0000
	(0.006)	(0.005)	(0.005)	(0.004)
Month fixed effects	Included	Included	Included	Included
Company fixed effects	Included	Included	Included	Included
Type fixed effects	Included	Included	Included	Included
Constant	0.022	0.001	-1.179***	-1.417***
	(0.056)	(0.050)	(0.060)	(0.054)
Likes	-	-	0.041***	0.059***
			(0.004)	(0.002)
Comments	0.089***	0.101***	-	-
	(0.004)	(0.005)		
N	135,927	219,190	135,927	219,190
Pseudo R^2	0.148	0.121	0.096	0.075

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors included in parentheses.

We ran quantile regressions for count dependent variables (Geraci 2016) on both short-term and long-term data, separately for user posts with and without Reactions. Because the distributions of Likes and Comments across user posts are extremely skewed (i.e., following the "long-tail" shape), we estimated the regressions at 90%, 95%, and 99% quantiles. The short-term and long-term results are included in Tables 14 and 15. Note that we did not report Pseudo R^2 measures for quantile regressions, because they were estimated using the Frisch–Newton interior point method (Geraci 2016), rather than maximum likelihood (which is needed to compute the McFadden's Pseudo R^2 measure).

Results of the quantile regressions are largely the same as our main results. For user posts that received Reactions, the effects on Likes and Comments are significantly positive across all three quantiles. For posts that did not receive Reactions, the effects on Likes and Comments are negative across all three quantiles. The only exception was that the effects for posts without Reactions are not statistically significant in the short-term analysis, possibly due to the relatively small sample size. Overall, this set of robustness check results further demonstrated the validity of our previous findings. In particular, the effects of Reactions on Likes and Comments not only existed "on average", but could also be detected across several key quantiles.

Table 14. Short-Term Quantile Regression Estimation Results

	DV = Likes					
	Posts with Reactions			Posts without Reactions		
	90%	95%	99%	90%	95%	99%
After	**1.107*** (0.095)**	**1.222*** (0.174)**	**1.297*** (0.274)**	**-0.011 (0.025)**	**-0.015 (0.029)**	**-0.032 (0.051)**
Length	0.002*** (0.0002)	0.001*** (0.0002)	0.001+ (0.001)	0.002*** (0.0002)	0.002*** (0.0001)	0.001** (0.0004)
Positive	0.010** (0.004)	0.010 (0.006)	0.004 (0.005)	0.007** (0.003)	0.006** (0.002)	0.012+ (0.006)
Negative	0.030*** (0.005)	0.018** (0.007)	0.014+ (0.008)	0.031 (0.004)	0.026 (0.004)	0.025*** (0.005)
UGC	0.003*** (0.001)	0.002* (0.001)	0.0001 (0.002)	0.001 (0.0002)	0.001 (0.0002)	0.0003 (0.0004)
MGC	-0.005 (0.017)	-0.010 (0.020)	0.040 (0.040)	-0.032** (0.012)	-0.022* (0.011)	-0.005 (0.027)
Company fixed effects	Included	Included	Included	Included	Included	Included
Type fixed effects	Included	Included	Included	Included	Included	Included
Constant	-0.430** (0.135)	0.250 (0.186)	0.961** (0.315)	-0.104 (0.098)	0.406*** (0.111)	1.154*** (0.214)
	DV = Comments					
	Posts with Reactions			Posts without Reactions		
	90%	95%	99%	90%	95%	99%
After	**0.913*** (0.116)**	**0.882*** (0.091)**	**0.529*** (0.142)**	**-0.030 (0.026)**	**-0.004 (0.032)**	**-0.058 (0.050)**
Length	0.001*** (0.0003)	0.002*** (0.0003)	0.001** (0.001)	0.002*** (0.0002)	0.002*** (0.0002)	0.002** (0.001)
Positive	-0.047*** (0.005)	-0.041*** (0.004)	-0.031*** (0.006)	-0.040*** (0.004)	-0.030*** (0.004)	-0.019*** (0.005)
Negative	0.015* (0.005)	0.010+ (0.005)	-0.005 (0.013)	0.012** (0.004)	0.013* (0.005)	0.013 (0.010)
UGC	-0.003*** (0.001)	-0.002*** (0.001)	-0.002 (0.001)	-0.002*** (0.0003)	-0.002*** (0.0003)	-0.001** (0.0004)
MGC	0.003 (0.019)	-0.008 (0.023)	0.003 (0.030)	0.010 (0.012)	0.003 (0.015)	0.014 (0.019)
Company fixed effects	Included	Included	Included	Included	Included	Included
Type fixed effects	Included	Included	Included	Included	Included	Included
Constant	-0.451 (0.356)	0.426+ (0.252)	1.398*** (0.317)	-0.542* (0.228)	0.215 (0.164)	1.126*** (0.224)

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors included in parentheses.

5.6. Exploratory Content Analyses

Although our analyses showed an overall reinforcement effect of the Reactions feature on Likes and Comments for posts that received Reactions, we could not entirely exclude the possibility of a substitution effect. It is possible that the reinforcement effect and the substitution effect co-exist, and jointly determine the overall engagement for a user post. For example, for a given user post, some Likes and Comments may have been substituted by Reactions, but even more Likes and Comments may be generated due to the reinforcement effect of Reactions, resulting in an overall increase in Likes and Comments. In this section, we conducted an exploratory content analysis of Comments to offer a preliminary assessment of the potential *substitution* effect at the individual post level.

Table 15. Long-Term Quantile Regression Estimation Results

DV = Likes						
	Posts with Reactions			Posts without Reactions		
	90%	95%	99%	90%	95%	99%
After	**0.316*** (0.046)**	**0.228*** (0.056)**	**0.312*** (0.092)**	**-0.659*** (0.027)**	**-0.735*** (0.029)**	**-0.719*** (0.056)**
Length	0.001*** (0.0001)	0.001*** (0.0001)	0.001*** (0.0001)	0.001*** (0.0001)	0.001*** (0.0001)	0.001*** (0.0001)
Positive	0.012*** (0.001)	0.012*** (0.002)	0.013* (0.005)	0.011*** (0.001)	0.010*** (0.001)	0.012*** (0.002)
Negative	0.038*** (0.002)	0.029*** (0.002)	0.018*** (0.004)	0.039*** (0.001)	0.032*** (0.002)	0.019*** (0.003)
UGC	0.001*** (0.0000)	0.001*** (0.0000)	0.0004*** (0.0000)	0.001*** (0.0000)	0.001*** (0.0000)	0.001*** (0.0001)
MGC	-0.048*** (0.005)	-0.044*** (0.005)	-0.015 (0.011)	-0.046*** (0.004)	-0.047*** (0.004)	-0.013 (0.008)
Month fixed effects	Included	Included	Included	Included	Included	Included
Company fixed effects	Included	Included	Included	Included	Included	Included
Type fixed effects	Included	Included	Included	Included	Included	Included
Constant	0.626*** (0.075)	1.271*** (0.071)	2.188*** (0.100)	0.686*** (0.060)	1.316*** (0.060)	2.127*** (0.073)
DV = Comments						
	Posts with Reactions			Posts without Reactions		
	90%	95%	99%	90%	95%	99%
After	**0.984*** (0.033)**	**0.805*** (0.042)**	**0.487*** (0.067)**	**-0.211*** (0.024)**	**-0.247*** (0.026)**	**-0.298*** (0.041)**
Length	0.001*** (0.0001)	0.002*** (0.0001)	0.002*** (0.0001)	0.001*** (0.0001)	0.001*** (0.0001)	0.001*** (0.0001)
Positive	-0.032*** (0.002)	-0.024*** (0.002)	-0.014*** (0.003)	-0.033*** (0.001)	-0.025*** (0.002)	-0.017*** (0.002)
Negative	0.014*** (0.002)	0.012*** (0.002)	0.019*** (0.005)	0.010*** (0.001)	0.010*** (0.002)	0.011** (0.004)
UGC	-0.0001** (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)
MGC	0.003 (0.005)	0.001 (0.005)	-0.008 (0.007)	0.004 (0.004)	-0.001 (0.004)	-0.002 (0.006)
Month fixed effects	Included	Included	Included	Included	Included	Included
Company fixed effects	Included	Included	Included	Included	Included	Included
Type fixed effects	Included	Included	Included	Included	Included	Included
Constant	-0.384*** (0.070)	0.244*** (0.067)	1.132*** (0.096)	-0.551*** (0.061)	0.154* (0.063)	1.012*** (0.080)

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors included in parentheses.

If the substitution effect does occur on a substantial scale, then we should observe systematic differences in the Comments associated with posts before and after the feature change. Specifically, if the Reactions feature was used as intended, they might have been used to substitute for short comments such as "Love it!", "so sad", or "I feel angry!" As a result, the comments after the feature change should be longer on average, and contain fewer mentions of words "love", "haha", "wow", "sad", and "angry" or the synonyms and variations of these words, than what the comments would have been before the feature change.

We took the 5,924 user posts created within the 6 months after feature change that had at least one Reaction and at least one Comment, and used propensity score matching to create a matched sample among posts before the feature change. The matching process was the same as discussed before. Then, we compared the Comments associated with user posts in the two matched samples on the following attributes: (1) average length of the Comments; (2) average counts of each of the five words: "love", "haha", "wow", "sad", and "angry", as well as their synonyms and simple variations among Comments. For each of the above five words, we counted direct mentions of it, mentions of its synonyms (e.g., "affection" was counted as mentions of "love"), and mentions of its simple variations (i.e., any words that have the focal word as a sub-string, e.g., "hahaha" was counted as mentions of "haha"). We combined two sources to construct the list of synonyms. First, we looked up the Merriam-Webster thesaurus and Thesaurus.com to include all synonyms for each of the five words. Second, we used the "Sentiment and Emotion Lexicons" (EmoLex) developed by Mohammad et al. (2010), which contains a large collection of words and whether each word is associated with each of ten emotion categories.[11] We incorporated all anger-associated words for the "angry" Reaction, joy-associated words for the "haha" Reaction, sadness-associated words for the "sad" Reaction, and surprise-associated words for the "wow" Reaction. There is not a very clear correspondence between the emotion categories and the "love" Reaction, so we did not include any. We provide the descriptions of synonyms in Table 16 and the results in Table 17.

As shown in Table 17, there were systematic differences between matched pre-change Comments and post-change Comments of user posts that received Reactions. However, the differences were not all consistent with our expectations. On the one hand, Comments after the feature change contained fewer mentions of the five Reaction words as well as their synonyms and variations, suggesting that the new Reaction buttons may have substituted some Comments with overlapping emotional words. On the other hand, contrary to our expectations, Comments after the feature were *shorter* on average, instead of longer. Overall, our exploratory content analyses indicate that the substitution effect may have co-occurred with the reinforcement effects, but it was comparatively weak. As a result, we still observed an overall positive impact of Reactions on Comments for posts that had received them.

Table 16. Synonyms Considered in Exploratory Content Analysis of Comments

Keyword	Synonyms
Love	20 synonyms from Merriam-Webster thesaurus: {affection, attachment, devotedness, devotion, fondness, passion, beloved, darling, dear, flame, hon, honey, sweetheart, sweet, sweetie, fancy, favor, like, liking}
Haha	7 synonyms from Thesaurus.com: {humor, laugh, trick, play, antic, gag, farce} and 690 synonyms from EmoLex
Wow	6 synonyms from Thesaurus.com: {wow, amuse, delight, charm, entertain, awe} and 534 synonyms from EmoLex
Sad	34 synonyms from Merriam-Webster thesaurus: {bad, blue, brokenhearted, crestfallen, dejected, depressed, despondent, disconsolate, doleful, down, downcast, downhearted, droopy, forlorn, gloomy, glum, heartbroken, heartsick, heartsore, heavyhearted, inconsolable, joyless, melancholic, melancholy, miserable, mournful, saddened, sorrowful, sorry, unhappy, woebegone, woeful, wretched} and 1191 synonyms from EmoLex
Angry	30 synonyms from Merriam-Webster thesaurus: {angered, apoplectic, ballistic, choleric, enraged, foaming, fuming, furious, hopping, incensed, indignant, inflamed, infuriate, infuriated, irate, ireful, livid, mad, outraged, rabid, rankled, riled, riley, roiled, sore, steaming, ticked, wrathful, wroth} and 1247 synonyms from EmoLex

[11] The ten emotion categories are: anger, anticipation, disgust, fear, joy, negative, positive, sadness, surprise, and trust.

Table 17. Exploratory Content Analysis of Comments

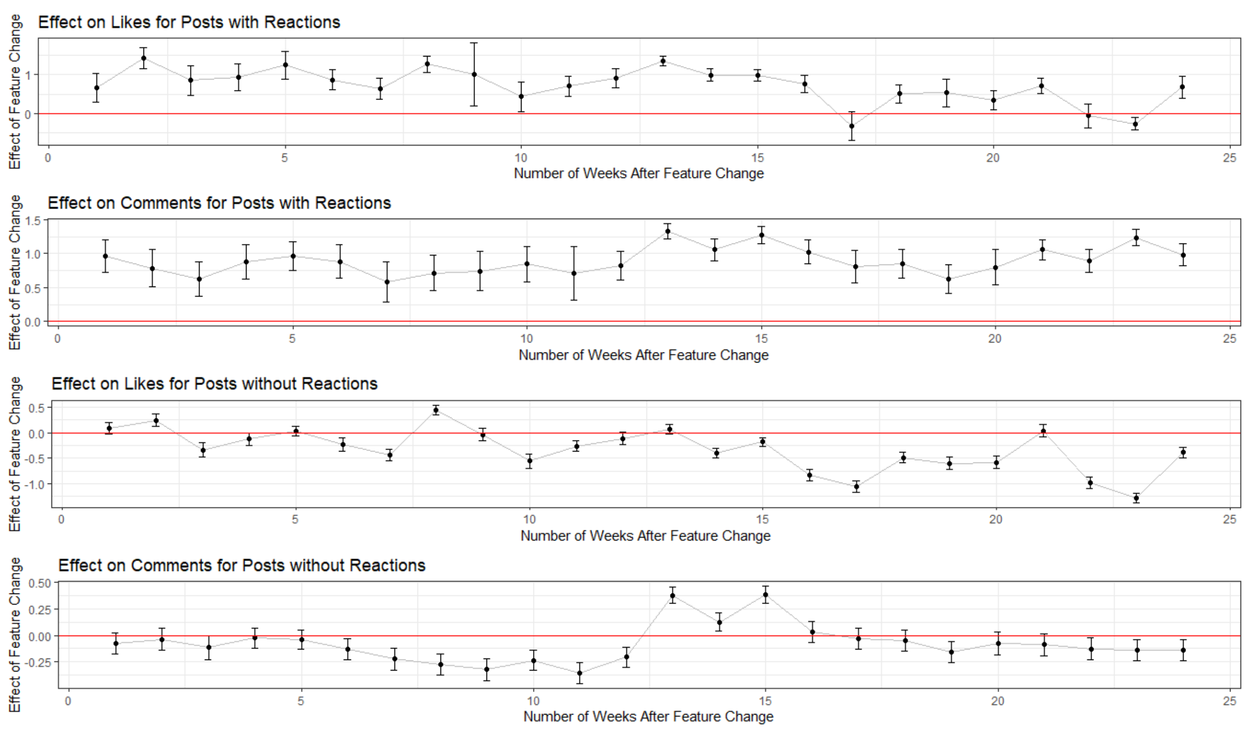
	Propensity Score Matching				
	Before	After	t-test	Cohen's *d*	% change
Average Comment Length	35.10	29.77	***	0.226	-15.2%
Average counts of *love* and synonyms and variations	0.198	0.168	***	0.095	-15.2%
Average counts of *haha* and synonyms and variations	0.601	0.529	***	0.185	-12.0%
Average counts of *wow* and synonyms and variations	0.540	0.450	***	0.226	-16.7%
Average counts of *sad* and synonyms and variations	0.748	0.671	***	0.219	-10.3%
Average counts of *angry* and synonyms and variations	0.675	0.653	**	0.059	-3.3%

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.7. Weekly Estimations of Effects

Throughout the paper, we have chosen the time window of 4 weeks to represent the short term and 6 months to represent the long term. In this robustness check, we moved beyond these dichotomous definitions of short term vs. long term, and estimated the effects of Reactions feature at the weekly scale through our entire data collection period. More specifically, we used posts created within k weeks before and k weeks after the feature change, where $k \in \{1, \dots, 24\}$, to estimate the effects of the Reactions feature on Likes and Comments. Again, we analyzed posts with and without Reactions separately using the same Poisson regression specification as in our long-term analyses, except with weekly fixed effects rather than monthly fixed effects. We plotted the estimated coefficients and their confidence intervals in Figure 6.

Figure 6. Weekly Estimations of the Impact of the Reactions Feature



Note. In each subfigure, a dot represents an estimated coefficient on the impact of Reactions feature for a particular weekly time window. Vertical bars mark the 95% confidence interval of an estimation.

We can see from Figure 6 that, across the 24 weeks after the introduction of Reactions feature, its impact on Likes and Comments was largely consistent with our findings from previous analyses. There are a few cases that deviate from our findings, mostly notable during weeks 13-15 after the feature change, where posts *without* Reactions received *more* comments than what they would have received before the feature change. We notice, however, a similar "spike" was also observed for posts *with* Reactions during the same time period. It is possible that certain external events at that time had boosted commenting for a large number of posts (with or without Reactions). Moreover, even during those weeks, we still see that the positive effect of Reactions on Comments is stronger for posts with Reactions than those without Reactions. In general, our major findings stay robust when estimated at a much more granular time scale.

6. GITHUB: EXAMINING THE IMPACT OF THE REACTIONS FEATURE IN A NEW SETTING

In this section, we extend the scope of our research by considering another online platform, GitHub, where a similar Reactions feature was introduced. GitHub is one of the largest online platforms for software hosting and development. Besides hosting software projects, GitHub also serves as a social platform that allows developers and users of the software to discuss potential issues about the software, such as bugs, feature requests, and questions. Much like Facebook business pages where users interact with each other around brands, users on GitHub interact with each other around software projects. Such similarity in the nature of social interactions makes GitHub a suitable context to assess the generalizability of our findings.

Each project on GitHub has an "Issues" page, where developers can post issues and other developers can comment to offer suggestions or solutions. On March 10, 2016, GitHub introduced six Reaction buttons including "+1", "-1", "smile", "confused", "heart", and "tada" (Boxer 2016).[12] The Reactions feature is intended to "help people express their feelings more simply and effectively" (Boxer 2016). Similar to our analyses of Facebook business pages, we seek to understand the impact of the Reactions feature on developer engagement. More specifically, we ask: *how does the introduction of the Reactions feature on GitHub affect the amount of comments received by an issue (i.e., the existing engagement in this context)*?

To answer this question, we focused on the top 5 most popular software projects on GitHub, including tensorflow, bootstrap, vue, Facebook react, and ohmyzsh.[13] Using GitHub's API tool, we retrieved all the issues of these projects, posted 6 months before to 6 months after the introduction of the Reactions feature, i.e., 09/10/2015 – 09/10/2016. We only included "closed" issues, because the discussions of "open" issues were still ongoing. In total, we collected 7,608 issues from the 5 projects.

For a given issue i, we created several variables to describe its characteristics. $Length_i$, $Positive_i$ and $Negative_i$ respectively represent the word count, percentage of positive words, and percentage of negative words (labeled using LIWC) of the issue. $NumCodeBlock_i$ is the number of code blocks included in the issue text, which serves as a proxy for the technical sophistication of the issue, and $NumLabels_i$ measures the number of labels assigned by the project owner such as "bug", "question", or "enhancement" (issues with more labels may attract more attention and engagement). Furthermore, we created a dummy variable $After_i$ to indicate whether the issue was created before or after the feature change. We also included dummy variables $Project_i$ and $Month_i$ as project-level and month-level fixed effects. The dependent variable, $NumComments_i$, is the total number of comments received by the issue. The following regression specification is used:

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[12] Later on, GitHub added two more Reaction buttons, namely "rocket" and "eye".

[13] We located the top 5 software projects that received the highest number of stars as of 01/04/2020 (https://github.com/search?o=desc&q=stars%3A%3E1&s=stars&type=Repositories). We ignored popular non-software projects, such as coding resource lists and programming books.

$$NumComments_i = \beta_0 + \beta_1\, After_i + \beta_2\, Length_i + \beta_3\, Positive_i + \beta_4\, Negative_i + \beta_5\, NumCodeBlock_i + \beta_6\, NumLabels_i + \boldsymbol{\Psi}\, Month_i + \boldsymbol{\Gamma}\, Project_i + \varepsilon_i$$

To account for potential heterogeneity in the effects of feature change, we conducted separate analyses of issues that received at least one Reaction and issues that did not receive any Reactions. We estimated a Poisson regression specification for each. The results are summarized in Table 18.

Table 18. Reactions for GitHub Issues: Poisson Regression Estimation Results

	Issues with Reactions	Issues without Reactions
After	**0.453**** **(0.172)**	**-0.385***** **(0.094)**
Length	0.0002* (0.0001)	0.0001** (0.0000)
Positive	0.239 (0.322)	0.005 (0.245)
Negative	0.478 (0.339)	0.407+ (0.245)
NumCodeBlock	0.448*** (0.054)	0.136 (0.132)
NumLabels	0.278*** (0.034)	0.307*** (0.024)
Month fixed effects	Included	Included
Project fixed effects	Included	Included
Constant	0.670*** (0.111)	0.747*** (0.093)
N	4,058	6,987
Pseudo R^2	0.121	0.067

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors included in parentheses.

We found similar heterogeneous effects of the Reactions feature. For issues that received Reactions, they ended up also receiving significantly more comments than what they would have received before the feature change ($\beta_1 = 0.453$, $p < 0.01$). In contrast, for issues that were created after the feature change but did not receive any Reactions, they ended up receiving significantly fewer comments than what they would have received before the feature change ($\beta_1 = -0.385$, $p < 0.001$). We repeated the analyses with coarsened exact matching, using *Length*, *Positive*, *Negative*, *NumCodeBlock*, *NumLabels*, and *Project* as matching covariates, and obtained similar results. Issues with Reactions received significantly more comments than pre-change matched issues ($Mean_{before} = 4.718$, $Mean_{after} = 9.497$, $p < 0.001$, Cohen's $d = 0.57$, percentage change 101.3%). Issues without Reactions received fewer comments than pre-change matched issues ($Mean_{before} = 4.692$, $Mean_{after} = 4.466$, $p = 0.141$, Cohen's $d = 0.04$, percentage change −4.8%), although the effect was very small and statistically insignificant at 10% level.[14]

The GitHub data and analyses largely replicated our findings from Facebook business pages. Despite the various differences between Facebook business pages and GitHub issues pages (e.g., content, participants, and interface designs), we found essentially the same patterns of how engagement activities change after

[14] The lack of statistical significance is likely due to the combination of a small effect size to be detected and a relatively small size of the matched sample. In particular, for content that did not receive Reactions, the Facebook matched samples had around 188K observations, whereas the GitHub matched samples had around 6.8K observations.

the new Reactions feature was introduced. This demonstrates that our key findings regarding the impact of introducing the Reactions feature are not unique to Facebook business pages and can be generalized to other online platforms.

7. DISCUSSION

Engagement with user-generated content on social media takes place via engagement features, such as Likes and Comments. In this paper, we studied a new engagement feature on Facebook, known as the Reactions feature, and its impact on overall engagement and the use of existing engagement features. The Reactions feature allowed users to express more granular emotions that cannot be appropriately expressed by Likes, while also keeping the cost of engagement lower than writing Comments. By comparing user posts created before the feature change with user posts created after the feature change, we found the newly introduced Reactions feature was associated with an increase in overall engagement activities. We also found that the introduction of the Reactions feature affects the usage of existing engagement features such as Likes and Comments, and the effects of Reactions on Likes and Comments were heterogeneous across user posts. Specifically, user posts that received Reactions also ended up receiving more Likes and more Comments than what they would have before the feature change, which provided evidence for a reinforcement effect. In contrast, posts that were created after the change and did not receive any Reactions ended up receiving fewer Likes and fewer Comments than what they would have received before the feature change, although the effect sizes were small. These effects persisted for at least six months after the introduction of the new feature. We conducted multiple robustness checks and additional analyses to demonstrate the validity of our findings. Our major results were consistently replicated with several different empirical models and stayed robust against alternative explanations. In addition, exploratory content analysis of the Comments suggests that reinforcement and substitution effects may coexist, and the substitution effect was weaker than the reinforcement effect.

One possible explanation for the heterogeneous effects of the Reactions feature may be the process of "attention redistribution". Because users have limited time and attention to spend on Facebook business pages, they need to choose which content to engage with, and existing engagement can serve as metavoicing or signals for the quality or popularity of the content. As we have discussed before, while Likes, Comments, and Reactions are all metavoicing activities, they differ in cognitive effort and emotional complexity. The Reactions feature is unique because (1) it requires less cognitive effort than commenting and thus increases the likelihood of initial engagement; and (2) it communicates a richer set of emotions that is more granular than Likes and easier to process than Comments, and thus is more likely to attract attention. As a result, user posts with Reactions may be perceived as more engaging than user posts without Reactions and attract greater subsequent engagement. Meanwhile, as users devote more attention to posts with Reactions, less attention is spared for posts without Reactions. It seems that Reactions serving as metavoicing may lead to a "rich-get-richer" pattern in content engagement. Further unpacking the exact causal mechanisms behind the interplay of these features and understanding the pros and cons of engagement features as metavoicing represent interesting directions for future research.

Besides our main analyses of Facebook business pages, we also examined the effects of introducing a similar Reactions feature on GitHub issues pages. Despite significant differences between the two platforms, we found highly consistent patterns that the multiple engagement features were not independent. The introduction of a new feature like Reactions reinforced the use of other existing features for content that had attracted Reactions. In contrast, content that did not receive Reactions also received less engagement of other kinds, although the effect sizes were small. This extended study shows that our main findings can be generalized beyond our research setting to other social media platforms, especially online communities organized around user-generated content, shared interests or identities. However, cautions need to be taken to generalize our findings to online social networks organized primarily around interpersonal relationships, such as Facebook users' personal pages. Robust identification of the effects of Reactions on Facebook personal pages likely requires experimental methods, due to the unobserved confounding factors of Facebook's proprietary content recommendation algorithm.

Our findings have practical implications for social media platforms as well as the organizations that use social media to engage and interact with stakeholders. For social media platforms, it is useful to be cognizant about the behavioral consequences of a new design feature. As we have shown in this paper, introducing a new feature can have broad consequences on user behaviors, both through its own usage and through its interplay with other preexisting features. While some of these consequences are desirable (e.g., increased overall engagement), others may not have been intended (e.g., a "rich-get-richer" engagement pattern). Understanding how users actually use new features can help the platforms with designing meaningful new features and properly measuring their effectiveness. For organizations, our results indicate that user-generated content with some existing engagement is likely to attract even more engagement. Organizations can use such knowledge to strategize and prioritize their resources to respond to user-generated content, especially the content that has already received engagement.

To summarize, our paper contributes novel insights regarding the design of social features and their impact on user engagement behaviors. We provide empirical evidence on the interplay of multiple engagement features and demonstrate that the use of different engagement features is interdependent. This sheds new light on the trade-off between feature richness and complexity in the design of platform interfaces. On the one hand, introducing a new engagement feature provides the users with a new way of expressing themselves and interacting with others. On the other hand, it can also change the use of existing engagement features as users adapt to a richer set of features, and the effects can be long lasting. The cognitive effort and emotion complexity associated with a feature affect how it is used and how it influences the use of other engagement features. These factors should be considered when designing and introducing new engagement features.

Our work is not without limitations, many of which can be viewed as interesting and promising opportunities for future studies. First, while our main analyses examined Reactions feature as a whole without differentiating which Reaction buttons were used, we did observe that different types of Reactions were not used equally (see Appendix B for summary statistics on each of the five Reactions). The relative frequency of different Reactions may depend on the sentiment of user posts and user preferences. Future research can drill deeper to each Reaction type, look for interesting engagement patterns, and get at more fine-grained understanding of individual Reactions. Second, we relied primarily on archival data from Facebook and GitHub for analyses. Future research can seek to conduct large scale field experiments to identify specific causal mechanisms and to extend to broader settings such as Facebook user feeds or other social media platforms. Third, we have only considered a single (albeit representative) feature change; future research may examine other instances or types of feature change in online platforms, and dive deeper into the behavioral or psychological antecedents for using different types of engagement features. Finally, our work represents a first step towards understanding the interplay between feature richness and complexity in the design of engagement features. More research is needed in this domain to guide the practices of designing meaningful features for user engagement.

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