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Brand post popularity on Facebook, Twitter, Instagram and LinkedIn: The case of start-ups

Abstract

Purpose: With the growing trend of omni-channel marketing, brands are increasingly looking to offer a seamless experience to their online fan base by connecting with them across multiple social media platforms. This paper explores the relationship between brand posts' characteristics and popularity for start-ups across four different social media platforms: Facebook, Twitter, Instagram and LinkedIn.

Design/methodology/approach: A total of 1,200 social media posts from 10 start-ups were subjected to content analysis. Regression analysis was employed with brand posts' popularity (Likes, Comments and Shares/Retweets) as the dependent variable.

Findings: The results reveal several nuances in brand post popularity for start-ups across Facebook, Twitter, Instagram and LinkedIn. Antecedents of the popularity measures of Likes, Comments and Shares/Retweets also fared differently.

Originality: The paper reports one of the earliest empirical studies to better understand how the qualities of brand posts are related to their appeal across multiple social media platforms. It advances the literature on social media marketing and offers insights to social media managers of brands, particularly start-ups, on how to offer smoother customer journeys across numerous digital touchpoints.

Keywords: brand post popularity; social media marketing; Facebook; Twitter; Instagram; LinkedIn; start-up.

Article classification: Research paper

1 Introduction

Social media has now transformed how consumers interact with brands. There are currently over 4.58 billion Internet users[1] who have the option to interact with their favorite brands online. This massive market has become so attractive for business purposes that brands continually seek ways to ensure that their social media posts grab the eyeballs of the online populace (Antoniadis et al., 2019; Coelho et al., 2016; De Vries et al., 2012; Dwivedi et al., 2021).

Much research has been done to understand the characteristics of brand posts that contribute to their popularity. Brand post popularity is defined as the extent to which the posts attract Likes, Comments and/or Shares (Banerjee and Chua, 2019; De Vries et al., 2012; Zadeh and Sharda, 2014). It is a key performance indicator for brands' social media presence. Brand posts that are not text-heavy and incorporate vivid imagery have been consistently shown to help promote popularity (De Vries et al., 2012; Sabate et al., 2014).

In the literature however, two research gaps still exist. First, most studies have concentrated on Facebook (e.g., Lin et al., 2017; Rahman et al., 2016), ignoring other social media platforms. This gap is important to plug because findings from Facebook cannot be generalized to other types of social media (Bonsón and Bednárová, 2013; Kietzmann et al., 2011), including microblogging sites (e.g., Twitter), rich media sharing sites (e.g., Instagram), and professional B2B networking sites (e.g., LinkedIn). The scientific understanding of how the qualities of brand posts are related to their appeal across numerous social media platforms is still limited. In consequence, social media brand managers are unsure of what works well on one platform but flounders on another.

Second, existing research has primarily focused on well-known brands (e.g., Mazloom et al., 2016), ignoring start-ups. Unlike well-known firms with a significant fan base, start-ups lack an established brand image. Therefore, what works for established brands may not apply to start-ups (Robson et al., 2022; Virtanen et al., 2017). Nevertheless, start-ups are important to study as they have globally generated a whopping $2.8 trillion in economic value over just two years prior to the COVID-19 pandemic and have clearly been on an upward trajectory (Stangler, 2019). As the economy gathers steam in the post-pandemic world, start-up funding surpassed $600 billion in 2021 (Jurgens, 2022). Furthermore, research shows that a strategic use of social media is imperative for start-ups (Virtanen et al., 2017). Therefore, as new entrants in the market, how start-ups' brand posts become popular on social media makes for an interesting revelation.

For these reasons, the objective of this paper is to explore the relationship between brand posts' characteristics and popularity for start-ups across four social media platforms: Facebook, Twitter, Instagram and LinkedIn. These platforms were chosen because of their inherently distinctive affordances (Bonsón and Bednárová, 2013; Kietzmann et al., 2011; Smith et al., 2012): Facebook, a social networking site, allows users to interact with the online peers. Twitter, a microblogging site, allows them to share updates but with stringent length restrictions. Instagram, a rich media sharing site, allows users to share photos and videos. LinkedIn, a professional networking site, allows them to develop their personal brand, specifically for B2B interactions. Moreover, several brands maintain their presence on each of the four popular platforms (Carter, 2020; Ennis-O'Connor, 2019). Also, these platforms had the greatest number of active users in 2019 (Kellogg, 2019).

The novelty and significance of the paper lies in its potential contributions to both theory and practice. On the theoretical front, the paper serves as a response to the research call to investigate posts' popularity of brands that are not necessarily supported by a huge fan base (Banerjee and Chua, 2019; Robson et al., 2022). Moreover, extending previous works that mostly focused on Facebook (e.g., Antoniadis et al., 2019; De Vries et al., 2012; Sabate et al., 2014), the paper obtained data from Facebook, Twitter, Instagram and LinkedIn. By examining 1,200 posts from 10 start-ups uniformly distributed across the four platforms, the findings enrich the scholarly understanding of start-ups' brand post popularity on social media.

On the practical front, the paper has the potential to illuminate how start-ups might make the most of social media to accelerate their growth. This is beneficial as new businesses are vital to the economy (Jurgens, 2022). For example, start-ups in a country such as India grew from around 7,000 in 2008 to some 50,000 by 2018 (KPMG, 2019). Alone in 2018, Chinese start-ups accounted for 47% of worldwide venture capital investments (Yang, 2018). Furthermore, the findings equip social media brand managers with a better understanding of nuances in brand post popularity across different social media platforms. This in turn can aid omni-channel marketing efforts—"the synergetic management of the numerous available channels and customer touchpoints, in such a way that the customer experience across channels and the performance over channels is optimized" (Verhoef et al., 2015, p. 176). Although omni-channel marketing is now a must for a seamless consumer experience (Payne et al., 2017; SAP Digital Experience Report, 2017), little scholarly attention has hitherto been trained to brands' social media presence across multiple digital touchpoints. Thus, we respond to the recent call for research to better understand the phenomena of social media marketing for the benefit of both academics and practitioners (Dwivedi et al., 2021).

2 Literature Review

2.1 Theoretical Background

A growing body of literature suggests that a brand's social media presence can affect its bottom line (Dwivedi et al., 2021; Rahman et al., 2016). For a favorable impact on its bottom line, a brand conceivably needs posts that become popular, i.e.; attract Likes, Comments and/or Shares (De Vries et al., 2012; Sabate et al., 2014). Informed by Banerjee and Chua (2019), we expect that presentation, engagement, brand awareness, and temporal characteristics of brand posts will have a bearing on the posts' popularity on social media.

First, presentation characteristics refer to properties that reflect how the message content in posts is delivered. The potential for the presentation category to have a bearing on posts' popularity is undergirded by the theory of framing (Druckman, 2001). Specifically, framing is an effect that occurs when a communicator presents a message strategically to a specific audience so as to serve a particular purpose. Framing effect has been documented in brand communications (Homer and Yoon, 1992; Tsai, 2007). Conceivably, start-ups would not frame their social media posts in any ad hoc manner. Instead, they would want to frame their messages in ways such that the entries would be perceived favorably by users on social media. For example, they could make the posts vivid and informative but not lengthy. The favorable perception may in turn contribute to posts' popularity.

Second, engagement characteristics refer to properties of posts that allow brands to interact with users. The potential for the engagement category to have a bearing on posts' popularity is undergirded by the attachment theory, which is valuable for marketers in evaluating customer-brand relationships (Hinson et al., 2019). The theory essentially suggests that to engage with a brand, one must experience a sense of attachment to the brand (Wallendorf and Arnould, 1988). Recent research shows that Facebook users' attachment to a brand drives them to engage with its Facebook page (Hinson et al., 2019). Meanwhile, as part of their relationship marketing efforts (Ashley et al., 2011; Rather, 2019), brands are now increasingly looking to engage with their fan base on social media to foster attachment. These could come in a variety of forms, ranging from calls to action and member tagging to deals and contests. Informed by the attachment theory, the interactions between brands and followers as facilitated through a post should therefore determine, at least in part, the popularity of the entry (De Vries et al., 2012; Hinson et al., 2019).

Third, brand awareness characteristics refer to properties of posts that allow brands to showcase their online presence. The potential for the brand awareness category to have a bearing on posts' popularity is supported by the notion of branding strategy (Aaker, 2004). Each brand has its own specific advantage, which helps it develop brand equity—the value of having a recognized brand among users. An integral part of brand equity is encompassed by brand awareness. It enhances the visibility and familiarity of the brand among individuals (Aaker, 2004). When a brand promotes itself through social media posts (e.g., by comparing itself with a competitor or highlighting its CSR efforts for reputation-building), this contributes to its brand awareness and in turn amplifies the likelihood of its posts to become popular (Swani and Milne, 2017). This could be particularly true for start-ups which do not have an established brand image, unlike well-established brands.

Finally, temporal characteristics encompass time-specific properties of posts. The potential for the temporal category to have a bearing on posts' popularity is undergirded by the social impact theory, which suggests that any impact depends on immediacy (Latané, 1981). Specifically, immediacy refers to the proximity in time between the object of influence and the target of influence. If a brand has a presence on social media, it has the opportunity to use fresh posts (object of influence) to attract the attention of (impact) its followers (target of influence) immediately. After all, online followers are now just a mobile device away from the brand that has the option of offering time-sensitive social media posts to endear attention. In other words, brands' content scheduling strategy on social media can dictate posts' popularity (Banerjee and Chua, 2019).

2.2 Related Works on Brand Post Popularity

De Vries et al. (2012) conducted one of the earliest works on the topic of brand post popularity, focusing on Facebook pages of 11 international brands. Antecedents such as vividness and interactivity enhanced posts' likelihood to become popular, measured as the number of Likes and Comments. This seminal work has been followed by a body of similar research over the past decade (e.g., Rahman et al., 2016; Sabate et al., 2014; Swani et al., 2013; Yu and Sun, 2019). While some measured brand post popularity in terms of Likes and Comments, others also included Shares (Chua and Banerjee, 2015).

As shown in Table I, this stream of literature has identified a variety of antecedents that contribute to brand post popularity. All of these antecedents can be grouped into one of the four categories of brand post characteristics as identified earlier: presentation, engagement, brand awareness, and temporal.

With respect to the presentation category, posts that are visually stimulating usually turn out to be more popular than those that are dull (De Vries et al., 2012). Post length is also important as wordy posts are not always appreciated by the online community (Sabate et al., 2014). Posts that are informative with brand/product information (De Vries et al., 2012), use functional or emotional appeal (Swani and Milne, 2017) and offer entertainment through humor (Mazloom et al., 2016) have been shown likely to become popular on social media.

With respect to the engagement category, posts that facilitate many-to-many communication online have been shown to work well (Yu and Sun, 2019). Posts that contain an explicit call to action (Rahman et al., 2017) or engage fans in a contest (Banerjee and Chua, 2019) promote popularity. Entries that ask questions can also help attract attention (Rahman et al., 2017). Posts that tag members of the online community in their posts, recognize contributions of their fans, or target a specific group of audience also do well in terms of popularity (Banerjee and Chua, 2019). Additionally, deals, discounts and giveaways when mentioned in posts enhance their likelihood to become popular (Geurin and Burch, 2017).

With respect to the brand awareness category, the presence of the brand name is an important predictor of brand post popularity (Swani et al., 2013). Posts in which the brand takes center stage are usually more likely to become popular than those in which the brand lies at the periphery (Geurin and Burch, 2017). In addition, posts that brands use to highlight their CSR efforts and compare themselves with competitors work well in terms of attracting attention (Banerjee and Chua, 2019).

With respect to the temporal category, reference to seasons and festivals along with the interval between two posts has implications for brand post popularity (Banerjee and Chua, 2019). Whether a post is submitted on weekday or weekend has also been shown to determine the popularity of posts (Zadeh and Sharda, 2014). In fact, the submission time of posts can also dictate the extent to which the entries become popular (Pinto and Yagnik, 2017).

2.3 The Current Study

In this paper, the relationship between brand posts' characteristics and popularity for start-ups across four different social media platforms—Facebook, Twitter, Instagram and LinkedIn—is explored. We treat this as an exploratory paper and refrain from positing specific directional hypotheses. This was necessary for two reasons.

First, Facebook has been the predominantly studied platform in this research area (e.g., Antoniadis et al., 2019; Lin et al., 2017; Sabate et al., 2014; Schultz, 2017; Swani and Milne, 2017), with very few exceptions. While Twitter (Zadeh and Sharda, 2014) and Instagram (Coelho et al., 2016; Geurin and Burch, 2017; Yu and Sun, 2019) have been occasionally studied, there exist no studies that have examined brand posts' popularity on LinkedIn. Since these platforms offer disparate affordances (Bonsón and Bednárová, 2013;

Kietzmann et al., 2011; Smith et al., 2012), the knowledge available on Facebook cannot be extrapolated to the others.

Second, most research has focused on brands that are well-known, and hence likely to have a large fan base. For example, the scope of Mazloom et al. (2016) was trained on the likes of McDonalds and Burger King. Similarly, Swani and Milne (2017) focused on Fortune 500 brands. Start-ups have never received scholarly attention in this area even though they are crucial for economic growth (KPMG, 2019; Stangler, 2019; Yang, 2018). Furthermore, start-ups usually lack the knowledge, time and vision to integrate social media into their marketing efforts (Ghezzi et al., 2016; Virtanen et al., 2017). Clearly, findings on popular brands is inadequate to hypothesize the relationships for start-up brands' social media posts.

In sum, the literature on brand posts' popularity for start-ups across multiple social media platforms does not appear mature enough to formulate definitive hypotheses about the role of individual antecedents listed in Table I. Hence, nuances are left to be revealed through the empirical work that is presented next.

[Insert Table I around here]

3 Methodology

3.1 Data Collection

The focus of this research is on start-ups that have a presence on Facebook, Twitter, Instagram as well as LinkedIn. These platforms were chosen because they are not only popular among businesses but also had the greatest number of active users in 2019—2.38 billion for Facebook, 321 million for Twitter, 1 billion for Instagram, and 303 million for LinkedIn (Kellogg, 2019).

To select new brands, CrunchBase—a widely cited database of start-ups (Ghezzi et al., 2016; Liang et al., 2016)—was utilized in July 2019. The goal was to identify start-ups established in 2017. This would ensure that each of them had a comparable window to build its fan base.

In particular, CrunchBase helped identify all the 5,971 start-ups founded in 2017, arranged in decreasing order of their CrunchBase rank. To each start-up starting from the top of the list, the following inclusion criteria were applied: (1) It must be active on Facebook, Twitter, Instagram and LinkedIn, else it would not be apt for addressing the objective of this paper; (2) There must be at least 30 posts on each of the platform, ensuring a reasonable number of data points for analysis; (3) The posts must be in English as non-English posts are beyond the scope of this research. When a start-up met all the three inclusion criteria, it was added to the sample. If not, it was ignored. This iterative process continued until a list of ten start-ups was obtained (cf. table II).

[Insert Table II around here]

For each of the 10 start-ups, the follower count on the social media platforms was recorded. In addition, the most recent 30 posts (at the point of data collection: July-August 2019) on Facebook, Twitter, Instagram and LinkedIn were archived. Thus, there were 1,200 data points for analysis (10 start-ups x 4 social media platforms x 30 posts). The sample size compares favorably to related research (e.g., Geurin and Burch, 2017; Pinto and Yagnik, 2017; De Vries, Gensler, Leeflang, 2012).

For each post, the following fields were recorded: content of the post, submission day, as well as volumes of Likes, Comments and Shares (Retweets for Twitter). However, three exceptions are worth mentioning. One, submission day could not be identified for LinkedIn, which uses labels such as “3w” for posts submitted three weeks ago but does not provide the specific date. Two, number of Shares was not captured for Instagram, which does not have a Share functionality. Furthermore, LinkedIn has a Share functionality, but does not allow retrieving the Share count.

3.2 Coding of Variables

This paper sought to analyze antecedents of brand posts' popularity as exhaustively as possible. To this end, prior research helped us identify 21 variables (Table I). Of these, three were excluded, namely, entertainment, message appeal, and submission time. Entertainment and message appeal—especially emotions such as fear, romance, guilt, and sensuousness—are subjective parameters. Moreover, these emotions can be perceived differently by individuals from different cultures, which hence would hinder reliable coding. In other words, considering these variables could have taken a toll on the reliability of the data coding. Submission time was also excluded because it can be confounded by time zone differences.

Of the remaining 18 variables, four are conceptually similar: call to action, contest, interactivity, and question. All of these essentially require a follower to take an action. For example, a post with a call to action message may ask individuals to take part in a contest, interact with a post, or answer a question. To minimize conceptual overlaps, these four variables were merged and referred to as interactivity. Thus, we were left with 15 variables altogether.

Four of these 15 variables were measurable directly from the data: post length, member tagging, post interval, and submission day. Post length was measured based on the number of characters in posts. In terms of member tagging, posts were labelled as one if the tagging function of the social media platform was used; zero otherwise. Post interval was collected as the number of days between submission of the current post and that of the previous post. In terms of submission day, a post was coded as one if it was submitted during weekends, and zero if during weekdays. Post interval could not be calculated for LinkedIn which does not reveal the exact submission day.

The remaining 11 dimensions were measured using content analysis as this method has been widely used in related research (Swani and Milne, 2017; Sabate et al., 2014; De Vries, Gensler and Leeflang, 2012). The overall approach is informed by Krippendorf (1980). Table III presents the coding scheme for the 11 variables grouped based on the categories of presentation, engagement, brand awareness and temporal.

[Insert Table III around here]

The coding was done by one of the authors and an independent coder. All the 11 variables demonstrated sufficient inter-coder reliability. The average value of Cohen's Kappa was 0.86 (ranging from 0.79 for brand centrality to 1 for deal provision), which exceeds the acceptable threshold of 0.70 (Krippendorf, 1980).

After coding, it was found that two variables, namely, competitor comparison and targeted marketing, were coded as zero for all the 1,200 data points. Therefore, these could not be admitted for the final analyses.

3.3 Data Analyses

Hierarchical multiple regression was employed with each post as the unit of analysis. The dependent variable was brand posts' popularity. This was measured in terms of the volumes of Likes, Comments as well as Shares/Retweets where available. The unique start-ups (dummy-coded one through 10) and the size of their fan base—two brand-level attributes—were added as control variables.

Each dependent variable had five hierarchical models. Model 1 included the control variables. Model 2 through Model 5 encompassed the variables relating to the presentation category, the engagement category, the brand awareness category, and the temporal category respectively. Logarithm transformation was employed on all the continuous-scale variables (Sabate et al. 2014); i.e. the dependent variables, the control variable of follower count, post length, and post interval. All variance inflation factor values were below 10 and no pairwise correlations exceeded 0.6, thereby confirming no multicollinearity. For brevity, results are reported only for the final hierarchical model.

4 Results

4.1 Facebook

Table IV shows the hierarchical regression results for Facebook, on which the 10 start-ups had an average of 19,409 followers (*SD* = 18,688). With respect to Likes, statistically significant positive relationships arose for the presence of images ($\beta = 0.27$, $p < 0.01$) and videos ($\beta = 0.29$, $p < 0.01$). No significant relation was detected for Comments. With respect to Shares, statistically significant positive relationships emerged for the presence of images ($\beta = 0.19$, $p < 0.05$) as well as videos ($\beta = 0.32$, $p < 0.01$), links ($\beta = 0.17$, $p < 0.01$), brand centrality ($\beta = 0.18$, $p < 0.01$) and CSR ($\beta = 0.11$, $p < 0.05$).

[Insert Table IV around here]

4.2 Twitter

Table V shows the hierarchical regression results for Twitter, on which the 10 start-ups had an average of 4,339 followers (SD = 5,190). With respect to Likes, statistically significant positive relationships could be found for the presence of images ($\beta = 0.14$, $p < 0.05$) as well as animations ($\beta = 0.11$, $p < 0.05$), videos ($\beta = 0.26$, $p < 0.001$) and time-consuming call to actions ($\beta = 0.13$, $p < 0.01$).

With respect to Comments, statistically significant positive relationships could be found for informativeness ($\beta = 0.11$, $p < 0.05$) and time-consuming call to actions ($\beta = 0.19$, $p < 0.001$). In contrast, the number of Comments exhibited a statistically negative relationship with member tagging ($\beta = -0.18$, $p < 0.001$).

With respect to Retweets, statistically significant positive relationships could be found for the presence of images ($\beta = 0.13$, $p < 0.05$), animations ($\beta = 0.10$, $p < 0.05$) and videos ($\beta = 0.26$, $p < 0.001$). Furthermore, statistically significant positive relationships were found for posts that were informative ($\beta = 0.15$, $p < 0.01$), required trivial actions ($\beta = 0.14$, $p < 0.01$), or were time consuming ($\beta = 0.16$, $p < 0.01$).

[Insert Table V around here]

4.3 Instagram

Table VI shows the hierarchical regression results for Instagram, on which the 10 start-ups had an average of 12,656 followers (SD = 24,585). With respect to Likes, a statistically significant positive relationship could only be found for the presence of brand names ($\beta = 0.15$, $p < 0.001$). However, the number of Likes also showed statistically significant negative relationships with post length ($\beta = -0.11$, $p < 0.05$) as well as links ($\beta = -0.12$, $p < 0.01$) and trivial call to actions ($\beta = -0.10$, $p < 0.05$).

With respect to Comments, statistically significant positive relationships could be found for member recognition ($\beta = 0.13$, $p < 0.01$), deal provision ($\beta = 0.18$, $p < 0.001$) and brand centrality ($\beta = 0.09$, $p < 0.05$).

[Insert Table VI around here]

4.4 LinkedIn

Table VII shows the hierarchical regression results for LinkedIn, on which the 10 start-ups had an average of 5,122 followers (SD = 7,618). With respect to Likes, statistically significant positive relationships emerged for brand centrality ($\beta = 0.17$, $p < 0.001$) and CSR ($\beta = 0.08$, $p < 0.05$). Number of Likes also showed statistically significant negative relationships with post length ($\beta = -0.25$, $p < 0.001$), links ($\beta = -0.09$, $p < 0.05$) and posts that required trivial actions ($\beta = -0.08$, $p < 0.05$).

With respect to Comments, a statistically significant positive relationship could only be found for posts soliciting time-consuming actions ($\beta = 0.18$, $p < 0.001$). In contrast, the number of Comments showed statistically significant negative relationships with posts soliciting trivial actions ($\beta = -0.15$, $p < 0.01$) and those that were seasonally relevant ($\beta = -0.18$, $p < 0.001$).

[Insert Table VII around here]

4.5 Overall Exploratory Results

We broadly expected that presentation, engagement, brand awareness, and temporal characteristics of brand posts will have a bearing on the posts' popularity on social media. The empirical work paints a nuanced picture of how these categories of brand posts translate to post popularity for start-ups (Table VIII).

The presentation category worked in terms of the dimensions of informativeness (Comments and Retweets on Twitter), post length (Likes on Instagram and LinkedIn), and vividness (Likes and Shares/Retweets on both Facebook and Twitter). While informative and vivid posts promote popularity, lengthy posts do not seem to help.

The engagement category worked in terms of the dimensions of deal provision (Comments on Instagram), interactivity (Likes on Twitter, Instagram and LinkedIn; Comments on Twitter and LinkedIn; Shares on Facebook), member recognition (Comments on Instagram), and member tagging (Comments on Twitter). While posts that offer deals and appreciate members of the brand community promote popularity, those that tag a specific follower are not viewed favorably. Interactivity fared differently across the social media platforms. Posts that call for visiting a website works on Facebook but fails on LinkedIn. Those that call for trivial single-click actions work on Twitter but fail on Instagram and LinkedIn. Those that require time-consuming actions work on Twitter and LinkedIn.

The brand awareness category worked in terms of the dimensions of brand name (Likes on Instagram), brand centrality (Likes on LinkedIn; Comments on Instagram; Shares on Facebook), and CSR (Likes on LinkedIn; Shares on Facebook). All the three have a positive bearing on posts' popularity.

Little support was obtained with respect to the temporal category. This is largely inconsistent with prior studies conducted on well-established brands (Banerjee and Chua, 2019; Sabate et al., 2014). Only seasonally relevant posts on LinkedIn seem to mute Comments.

[Insert Table VIII around here]

5 Discussion and Conclusions

5.1 Findings in Light of the Literature

This paper sought to explore the relationship between brand posts' characteristics and popularity for start-ups across four social media platforms: Facebook, Twitter, Instagram and LinkedIn. The empirical work confirms reasonable explanatory power of the antecedents on all the four social media platforms—Facebook: Likes ($R^2 = 38.70\%$, adjusted $R^2 = 34.80\%$), Comments ($R^2 = 34.50\%$, adjusted $R^2 = 30.30\%$) and Shares ($R^2 = 31.00\%$, adjusted $R^2 = 26.60\%$); Twitter: Likes ($R^2 = 50.60\%$, adjusted $R^2 = 47.40\%$), Comments ($R^2 = 34.90\%$, adjusted $R^2 = 30.70\%$) and Retweets ($R^2 = 33.80\%$, adjusted $R^2 = 29.60\%$); Instagram: Likes ($R^2 = 57.30\%$, adjusted $R^2 = 54.70\%$) and Comments ($R^2 = 49.60\%$, adjusted $R^2 = 46.60\%$); LinkedIn: Likes ($R^2 = 64.90\%$, adjusted $R^2 = 62.90\%$) and Comments ($R^2 = 31.20\%$, adjusted $R^2 = 27.20\%$).

An inspection of the R^2 values further shows that the highest explanatory power on all the platforms was for Likes. In contrast, Shares lie at the other end of the spectrum. This could be attributed to nuances in the nature of the activities that require varying levels of cognitive involvement (Cvijikj and Michahelles, 2013). Liking is a quick single-click task. Comments call for relatively more cognitive efforts as one has to express oneself through free text. Shares on the other hand require not only a click but also a text, and hence can be deemed as the most challenging of the three activities. It seems that the lower the cognitive involvement in the task, the higher is the ability of the antecedents to predict brand posts' popularity, and vice-versa.

In terms of the presentation category, vivid posts submitted by start-ups generally drew more attention vis-à-vis those that lacked vividness on Facebook and Twitter. In particular, videos triggered the strongest effect on the number of Likes and Shares. This is consistent with the literature suggesting that visually captivating posts enhance brand posts' popularity (Banerjee and Chua, 2019; Schultz, 2017; Chua and Banerjee, 2015; Sabate et al., 2014; De Vries, Gensler and Leeflang, 2012). Mazloom et al. (2016) showed that post's popularity is dependent on their informativeness for well-known brands. Nevertheless, for start-ups, informativeness of posts did not have any bearing on their popularity on Facebook but made Comments and Retweets forthcoming on Twitter. Additionally, post length was negatively related to the likelihood of receiving Likes on Instagram and LinkedIn. Lengthy posts on social media do not augur well. In light of the theory of framing (Druckman, 2001), it is imperative that posts are kept succinct where possible, and framed using vivid cues to enhance their likelihood of becoming popular on social media.

With respect to the engagement category, the findings dovetail prior research. On the one hand, Cvijikj and Michahelles (2013) revealed that interactive posts tend to become popular. On the other hand, Sabate et al. (2014) showed that interactive posts that include a link had a negative impact on posts' popularity. Nevertheless, this paper found interactivity to work better on Facebook and Twitter than on Instagram and LinkedIn. Member recognition and deal provision were only helpful in eliciting Comments on Instagram. In light of the attachment theory (Wallendorf and Arnould, 1988), proactive relationship marketing efforts to foster brand attachment seems particularly conducive on social networking sites and microblogging sites, but caution is warranted on platforms meant for sharing photos or professional networking.

In terms of the brand awareness category, brand centrality was positively related to post popularity in terms of the number of Shares on Facebook and Likes on LinkedIn. This is in line with previous research suggesting that posts with the respective brand hogging the limelight are received more favorably than those in which the brand is featured only at the periphery (Swani and Milne, 2017). It also echoes previous findings from Geurin and Bruch (2017) and Mazloom et al. (2016), which showed that brands taking a brand focus (e.g. focusing on brand logo, brand name and product) were more successful in eliciting posts' popularity on Instagram. Banerjee and Chua (2019) showed that brands highlighting CSR efforts received greater number of Likes on Facebook. In contrast, this research shows that posts highlighting CSR contributions not only attracted Likes on LinkedIn but also Shares on Facebook. In light of branding strategy (Aaker, 2004), posts in which the brand makes its presence felt seem particularly helpful for start-ups.

In terms of the temporal category, no brand post characteristic positively predicted posts' popularity. Only seasonally relevant posts had a negative effect on LinkedIn. A possible explanation is that since LinkedIn is a platform meant for professional networking, it is used infrequently during festive seasons and holidays.

Furthermore, an inspection of the β coefficients (Table IV through Table VII) demonstrates that follower count was the strongest predictor of all the popularity metrics (Likes, Comments and Shares/Retweets) on all the four platforms. This suggests that start-ups must build a strong fan base in order to ensure that their posts stand a good chance to attract attention on social media.

Finally, the paper shows that presentation, engagement, brand awareness, and temporal properties of posts manifest differently on different social media platforms insofar as attracting popularity. On examining the change in variance explained, the presentation category emerged as being the most important predictor of posts' popularity on Facebook. On Twitter, the presentation category was the most important in drawing Likes and Retweets, but the engagement category was the most important in attracting Comments. On Instagram, the engagement category of antecedents was most important. On LinkedIn, the presentation category was the most important in drawing Likes, but the engagement category was the most important in attracting Comments.

5.2 Theoretical Contributions

This paper makes several theoretical contributions. First, it shows that brand post popularity is not an atomic concept but is very much context-dependent. For one, antecedents of popularity measures including Likes, Comments and Shares/Retweets fare differently perhaps due to their inherent differences. In addition, the paper confirms that findings from Facebook—the most widely studied platform hitherto—cannot be generalized to Twitter, Instagram and LinkedIn. Given that each platform offers disparate affordances, the nature of brand-related content on each is not the same (Smith et al., 2012). In consequence, the factors that predict their popularity on the platforms also vary. Thus, by considering how posts fare on multiple platforms, the paper enriches the understanding of brands' social media use from an omni-channel marketing perspective (Payne et al., 2017; Verhoef et al., 2015). This is particularly important at a point in time when consumers are increasingly using multiple channels to connect with their favorite brands (SAP Digital Experience Report, 2017).

Second, this paper is the first to empirically study what makes brand posts popular on LinkedIn. Previous studies have focused only on the likes of Facebook (e.g., Antoniadis et al., 2019), Twitter (e.g., Zadeh and Sharda, 2014), and Instagram (e.g., Coelho et al., 2016). In contrast, we unearth several new findings related to brand communications on LinkedIn, particularly from the perspective of start-ups. Likes seem possible to be promoted through short posts without any trivial interactivity (e.g., clicking a link). Brand centrality and CSR efforts can also be highlighted. Comments are thwarted by seasonal relevance. Additionally, while trivial interactivity muted Comments, time-consuming interactivity rendered them forthcoming. These findings open up new avenues for further research. Interviews could be conducted with LinkedIn users to better understand their motivations to connect with brands on the platform, their expectations, as well as how they respond to brand posts and why.

5.3 Practical Implications

With the growing trend of omni-channel marketing, brands are increasingly looking to offer a seamless experience to their online fan base by connecting with them across multiple social media platforms (Payne et al., 2017; SAP Digital Experience Report, 2017; Verhoef et al., 2015). To this end, the paper reports one of the earliest empirical works to better understand how brand posts' characteristics are related to their popularity across multiple social media platforms including Facebook, Twitter, Instagram and LinkedIn. In so doing, it offers insights to social media managers of brands, particularly start-ups, on how to offer smoother customer journeys through messaging across multiple touchpoints. This is important for a stronger and mutually reinforcing brand presence.

Specifically, findings from this research recommends start-ups to submit posts that are visually captivating by using vivid media such as videos and images. They could get creative with GIFs and meme culture. These can increase post's likelihood to garner Likes and Shares on Facebook and Twitter. However, to enhance the number of Likes on LinkedIn, start-ups must emphasize their CSR efforts, and allow the brand to hog the limelight in posts.

Furthermore, to attract Comments on posts submitted on LinkedIn, social media managers of start-ups should consider creating posts containing one or more questions. The findings also show that there are several post characteristics that would deter users from liking posts. For example, lengthy posts would lead to significantly less Likes on Instagram and LinkedIn. Therefore, social media mangers of start-ups should avoid submitting lengthy posts on Instagram and LinkedIn. Finally, given that the size of the fan base was a strong positive predictor of Likes, Comments and Shares/Retweets on all the four platforms, start-ups should develop proactive strategies encouraging individuals to follow their social media accounts.

5.4 Limitations and Future Research

Two limitations in this paper open up further research opportunities. First, this research did not consider the content of user comments. However, since communication on social media is bidirectional, it is an important aspect to investigate in order to get a better sense of the sentiment on the ground. Future research could address this limitation by collecting the content of user comments on brand posts and conducting a sentiment analysis.

Second, while collecting the number of Likes on Facebook and LinkedIn, the responses were treated as whole. In other words, the reactions behind Likes (e.g. sad, angry or funny) were ignored. In 2016 Facebook introduced its users to new reaction buttons, such as “love”, “haha”, “wow”, “sad” and “angry” (BBC, 2016). Later, in 2019, LinkedIn introduced additional reactions such as “celebrate”, “love”, “insightful” and “curious” (Chen, 2019). Future research could develop a more granular strategy that investigates brand posts’ popularity by considering these new reaction features.

Finally, to better understand start-ups’ omni-channel marketing efforts, future research could explore how brands convey the same information on different social media platforms, and the extent to which the nuances in messaging strategies translate to varying levels of popularity. Differences between start-ups and well-established brands could also be investigated.

Footnote

[1] https://www.internetlivestats.com/

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Table I: Antecedents of brand post popularity as identified from the literature.

Antecedents	Brief definitions
Presentation: Properties that reflect how the message content in posts is delivered	
Vividness	Visual stimulation (De Vries et al., 2012)
Post length	Wordiness (Sabate et al., 2014)
Informativeness	Prominence of brand/product information (De Vries et al., 2012)
Message appeal	Use of functional or emotional appeal (Swani and Milne, 2017)
Entertainment	Presence of humor (Mazloom et al., 2016)
Engagement: Properties of posts that allow brands to interact with users	
Interactivity	Many-to-many communication either between fans and brands or among fans (Yu and Sun, 2019)
Call to action	Posts urging fans to take an action (Rahman et al., 2017)
Contest organization	Notification about contests (Banerjee and Chua, 2019)
Question	Interrogative posts (Rahman et al., 2017)
Member tagging	Use of the tagging functionality (Banerjee and Chua, 2019)
Member recognition	Appreciation towards fans (Banerjee and Chua, 2019)
Targeted marketing	Focus on demographic slices (Banerjee and Chua, 2019)
Deal provision	Offer of discounts/incentives (Geurin and Burch, 2017)
Brand awareness: Properties of posts that allow brands to develop online presence	
Brand name	Brands mentioning their name (Swani, Milne and Brown, 2013)
Brand centrality	Brands taking center stage (Geurin and Burch, 2017)
Competitor comparison	Brands mention competitor brand(s) (Banerjee and Chua, 2019)
CSR	Brands as philanthropic contributors (Banerjee and Chua, 2019)
Temporal: Time-specific properties of posts	
Seasonal relevance	Reference to occasions/festivals (Banerjee and Chua, 2019)
Post interval	Interval between two posts (Banerjee and Chua, 2019)
Submission day	Weekday or weekend submission (Zadeh and Sharda, 2014)
Submission time	Time of day when posts are submitted (Pinto and Yagnik, 2017)

Table II: Final list of start-ups for data collection.

Start-up (Country)	Industry	Follower Count on Social Media
Acko (India)	Insurance	F: 54.8K, T: 11.2K, I: 4K, L: 15.8K
Yulu (India)	Transportation	F: 15.6K, T: 2.6K, I: 2.6K, L: 4.9K
Wild Earth (US)	Consumer Goods	F: 11.8K, T: 975, I: 5.9K, L: 961
Bank Open (India)	Banking	F: 30K, T: 1K, I: 304, L: 1.4K
Bird (US)	Transportation	F: 42.3K, T: 15.8K, I: 85.5K, L: 23.9K
Pie Insurance (US)	Insurance	F: 2.4K, T: 993, I: 630, L: 1K
Nreal (China)	Consumer Electronics	F: 1.3K, T: 1.5K, I: 8.1K, L: 853
Bridge Connector (US)	Health Care	F: 72, T: 229, I: 160, L: 717
Wyze (US)	Consumer Electronics	F: 33.9K, T: 8.2K, I: 11.3K, L: 1.2K
Neighborhood Goods (US)	Department Store	F: 1.6K, T: 713, I: 7.8K, L: 808

Note. F = Facebook, T = Twitter, I = Instagram, L = LinkedIn. Follower count represented in the order of K (that is, 10^3).

Table III: Coding scheme.

Antecedents	Coding procedure
Presentation	
Vividness[a]	1: Facebook/Twitter/LinkedIn post contains image 2: Facebook/Twitter/LinkedIn post contains animation 3: Facebook/Twitter/LinkedIn post contains video 0: Facebook/Twitter/LinkedIn post is text-only OR 1: Instagram post contains video 0: Instagram post contains image
Informativeness	1: Post contains information about products/services offered by the start-up 0: Otherwise
Engagement	
Interactivity[a]	1: Post contains URL asking fans to visit a website 2: Post asks users to take quick single-click actions beyond visiting a website 3: Post calls for more time-consuming interactions involving multiple clicks 0: Otherwise
Member recognition	1: Post appreciates the contributions of fans 0: Otherwise
Targeted marketing	1: Post focuses on specific demographic groups (e.g., female) 0: Otherwise
Deal provision	1: Post offers incentives or discounts 0: Otherwise
Brand awareness	
Brand name	1: Post includes the name of the start-up 0: Otherwise
Brand centrality	1: Post focuses on the start-up without necessarily referring to the name 0: Otherwise
Competitor comparison	1: Post compares the start-up with a competitor 0: Otherwise
CSR	1: Post reflects philanthropic efforts of the start-up 0: Otherwise
Temporal	
Seasonal relevance	1: Post refers to special occasions and festivals 0: Otherwise

Note. [a]When a post met multiple criteria, it was coded at the highest possible level.

Table IV: Standardized regression coefficients for Facebook (N = 300).

	Likes	**Comments**	**Shares**
#Follower	0.55***	0.47***	0.44***
*Presentation (*H1)			
Vividness (1: image)	0.27**	-0.05	0.19*
Vividness (2: animation)	-0.04	-0.02	0.02
Vividness (3: video)	0.29**	0.16	0.32**
Post length	0.01	-0.07	-0.08
Informativeness (1)	0.03	0.06	0.00
Engagement (H2)			
Interactivity (1: link)	-0.01	0.09	0.17**
Interactivity (2: trivial action)	-0.06	0.00	-0.06
Interactivity (3: time consuming)	-0.10	0.00	0.03
Member tagging (1)	-0.10	-0.10	0.03
Member recognition (1)	-0.05	-0.02	-0.10
Deal provision (1)	0.09	0.08	0.06
Brand awareness (H3)			
Start-up/brand name (1)	0.00	0.10	-0.01
Brand centrality (1)	0.09	0.03	0.18**
CSR (1)	0.07	0.09	0.11*
Temporal (H4)			
Seasonal relevance (1)	-0.01	-0.04	-0.01
Post interval	-0.04	-0.03	-0.07
Submission Day	-0.04	-0.10	-0.01
Variance explained			
Model 1 R^2 (ΔR^2)	30.30% (30.30%)	24.10% (24.10%)	17.80% (17.80%)
Model 2 R^2 (ΔR^2)	34.80% (4.50%)	29.50% (5.40%)	22.40% (4.60%)
Model 3 R^2 (ΔR^2)	37.30% (2.50%)	31.70% (2.20%)	26.50% (4.10%)
Model 4 R^2 (ΔR^2)	38.40% (1.10%)	33.40% (1.70%)	30.60% (4.10%)
Model 5 R^2 (ΔR^2)	38.70% (0.30%)	34.50% (1.10%)	31.00% (0.40%)

Note. ***p < 0.001; **p < 0.01; *p < 0.05. Model 1 = Control; Model 2 = Presentation; Model 3 = Engagement; Model 4 = Brand awareness; Model 5 = Temporal.

Table V: Standardized regression coefficients for Twitter (N = 300).

	Likes	**Comments**	**Retweets**
#Follower	0.54***	0.44***	0.36***
Presentation (H1)			
Vividness (1: image)	0.14*	-0.09	0.13*
Vividness (2: animation)	0.11*	-0.05	0.10*
Vividness (3: video)	0.26***	0.10	0.26***
Post length	0.09	0.07	0.04
Informativeness (1)	0.07	0.11*	0.15**
Engagement (H2)			
Interactivity (1: link)	-0.08	0.02	-0.03
Interactivity (2: trivial action)	0.06	0.09	0.14**
Interactivity (3: time consuming)	0.13**	0.19***	0.16**
Member tagging (1)	-0.03	-0.18***	0.04
Member recognition (1)	0.01	-0.01	-0.03
Deal provision (1)	0.01	0.02	0.04
Brand awareness (H3)			
Start-up/brand name (1)	0.05	0.05	0.08
Brand centrality (1)	0.02	0.00	0.02
CSR (1)	0.02	-0.01	0.02
Temporal (H4)			
Seasonal relevance (1)	-0.03	0.00	-0.04
Post interval	0.003	-0.02	-0.03
Submission Day	0.00	0.00	0.02
Variance explained			
Model 1 R^2 (ΔR^2)	40.10% (40.10%)	22.60% (22.60%)	18.20% (18.20%)
Model 2 R^2 (ΔR^2)	47.10% (7.00%)	27.10% (4.50%)	27.90% (9.70%)
Model 3 R^2 (ΔR^2)	50.10% (3.00%)	34.70% (7.60%)	32.70% (4.80%)
Model 4 R^2 (ΔR^2)	50.50% (0.40%)	34.90% (0.40%)	33.50% (0.80%)
Model 5 R^2 (ΔR^2)	50.60% (0.10%)	34.90% (0.00%)	33.80% (0.30%)

Note. ***p < 0.001; **p < 0.01; *p < 0.05. Model 1 = Control; Model 2 = Presentation; Model 3 = Engagement; Model 4 = Brand awareness; Model 5 = Temporal.

Table VI: Standardized regression coefficients for Instagram (N = 300).

	Likes	**Comments**
#Follower	0.69***	0.62***
Presentation (H1)		
Vividness (1: video)	0.08	0.00
Post length	-0.11*	-0.03
Informativeness (1)	-0.02	-0.03
Engagement (H2)		
Interactivity (1: link)	-0.12**	0.03
Interactivity (2: trivial action)	-0.10*	0.02
Interactivity (3: time consuming)	0.04	-0.03
Member tagging (1)	0.02	0.02
Member recognition (1)	-0.04	0.13**
Deal provision (1)	0.04	0.18***
Brand awareness (H3)		
Start-up/brand name (1)	0.15***	0.09
Brand centrality (1)	0.00	0.09*
CSR (1)	0.06	-0.01
Temporal (H4)		
Seasonal relevance (1)	-0.07	-0.07
Post interval	0.05	0.05
Submission Day	0.01	-0.05
Variance explained		
Model 1 R^2 (ΔR^2)	50.20% (50.20%)	41.80% (41.80%)
Model 2 R^2 (ΔR^2)	51.90% (1.70%)	42.60% (0.80%)
Model 3 R^2 (ΔR^2)	54.50% (2.60%)	46.90% (4.30%)
Model 4 R^2 (ΔR^2)	56.60% (2.10%)	48.70% (1.80%
Model 5 R^2 (ΔR^2)	57.30% (0.70%)	49.60% (0.90%)

Note. ***p < 0.001; **p < 0.01; *p < 0.05. Model 1 = Control; Model 2 = Presentation; Model 3 = Engagement; Model 4 = Brand awareness; Model 5 = Temporal.

Table VII: Standardized regression coefficients for LinkedIn (N = 300).

	Likes	**Comments**
#Follower	0.60***	0.38***
Presentation (H1)		
Vividness (1: image)	0.04	-0.03
Vividness (2: animation)	0.04	0.05
Vividness (3: video)	0.02	0.01
Post length	-0.25***	-0.04
Informativeness (1)	0.07	0.04
Engagement (H2)		
Interactivity (1: link)	-0.09*	-0.05
Interactivity (2: trivial action)	-0.08*	-0.15**
Interactivity (3: time consuming)	0.05	0.18***
Member tagging (1)	0.06	-0.02
Member recognition (1)	0.03	0.06
Deal provision (1)	-0.03	0.04
Brand awareness (H3)		
Start-up/brand name (1)	0.02	0.00
Brand centrality (1)	0.17***	0.11
CSR (1)	0.08*	0.07
Temporal (H4)		
Seasonal relevance (1)	-0.07	-0.18***
Variance explained		
Model 1 R^2 (ΔR^2)	53.90% (53.90%)	19.10% (19.10%)
Model 2 R^2 (ΔR^2)	58.60% (4.70%)	19.70% (0.60%)
Model 3 R^2 (ΔR^2)	61.60% (3.00%)	27.20% (7.50%)
Model 4 R^2 (ΔR^2)	64.50% (2.90%)	28.60% (1.40%
Model 5 R^2 (ΔR^2)	64.90% (0.40%)	31.20% (2.40%)

Note. ***p < 0.001; **p < 0.01; *p < 0.05. Model 1 = Control; Model 2 = Presentation; Model 3 = Engagement; Model 4 = Brand awareness; Model 5 = Temporal.

Table VIII: Findings with positive and negative predictors of brand post popularity.

	Platforms	Likes	Comments	Shares/Retweets
Presentation	Facebook	Positive: Vividness (image), Vividness (video) Negative: none	Positive: none Negative: none	Positive: Vividness (image), Vividness (video) Negative: none
	Twitter	Positive: Vividness (image), Vividness (video) Negative: none	Positive: Informativeness Negative: none	Positive: Vividness (image), Vividness (animation), Vividness (video), Informativeness Negative: none
	Instagram	Positive: none Negative: Post length	Positive: none Negative: none	Not applicable
	LinkedIn	Positive: none Negative: Post length	Positive: none Negative: none	Not applicable
Engagement	Facebook	Positive: none Negative: none	Positive: none Negative: none	Positive: Interactivity (links) Negative: none
	Twitter	Positive: Interactivity (time-consuming) Negative: none	Positive: Interactivity (time-consuming) Negative: Member tagging	Positive: Interactivity (trivial), Interactivity (time-consuming) Negative: none
	Instagram	Positive: none Negative: Interactivity (links), Interactivity (trivial)	Positive: Member recognition, Deal provision Negative: none	Not applicable
	LinkedIn	Positive: none Negative: Interactivity (links), Interactivity (trivial)	Positive: Interactivity (time-consuming) Negative: Interactivity (trivial)	Not applicable
Brand awareness	Facebook	Positive: none Negative: none	Positive: none Negative: none	Positive: Brand centrality, CSR Negative: none
	Twitter	Positive: none Negative: none	Positive: none Negative: none	Positive: none Negative: none
	Instagram	Positive: Brand name Negative: none	Positive: Brand centrality Negative: none	Not applicable
	LinkedIn	Positive: Brand centrality, CSR Negative: none	Positive: none Negative: none	Not applicable
Temporal	Facebook	Positive: none Negative: none	Positive: none Negative: none	Positive: none Negative: none
	Twitter	Positive: none Negative: none	Positive: none Negative: none	Positive: none Negative: none
	Instagram	Positive: none Negative: none	Positive: none Negative: none	Not applicable
	LinkedIn	Positive: none Negative: none	Positive: none Negative: Seasonal relevance	Not applicable