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Abstract
Purpose – The purpose of this paper is to measure the impact of post type (advertising, fan, events, information, and promotion) on two interaction metrics: likes and comments. The measuring involved two popular social media, Facebook and Instagram, and in business profiles of five different segments (food, hairdressing, ladies' footwear, body design, fashion gym wear).
Design/methodology/approach – The method used was multiple regression analysis with an estimator of the ordinary least squares for 1,849 posts from five different companies posted on Facebook (680 posts) and Instagram (1,169 Instagram) over an eight-month posting period. Regression analysis was used to identify the relationship between the dependent variables (likes and comments), and the independent variables (post typology, segments, week period, month, characters and hashtag).
Findings – It was seen that the post types events and promotion led to a greater involvement of followers in Instagram, in particular. In Facebook, the events post type was only significant in the like's interaction. Another finding of the research is the relevance of the food and body design segment which was significant in both virtual social media. This indicates a user preference involving their day-to-day lives, in this case, having a tattoo done or seeing a photo of a dessert.
Originality/value – With the findings of this study, academics and social media managers can improve the return indicators of interactions in posts and broaden the discussion on the types of post and interaction in different virtual social media.
Keywords Facebook, Comments, Social media, Instagram, Likes, Post typologies
Paper type Research paper

Introduction
Research focussing on social media has been producing considerable results about interaction and dynamics among individuals and companies, but it is still in its early stages, since "not even the term social media has a universally agreed definition, and there is no standard typology of social media platforms upon which everyone agrees" (Weller, 2015). Social media is being recognized as a tool and business managers advocate for its inclusion to the overall strategy because customers often rely on these platforms to interact with friends and brands (Rapp *et al.*, 2013). Despite being commonly used for research focussing on consumer metrics, preferences, and demand prediction (Aral *et al.*, 2013), challenges about the variety of user interactions in an ever-changing environment like social media still persist (Weller, 2015) and empirical efforts must address these issues.

Our research reconciles these challenges, as it considers brand content and individual user interaction across social media. Extant research about brand content and engagement metrics normally used single environments, reproducing the overall

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publication trend, where Facebook and Twitter are most overemphasized (Weller, 2015). Over the last years, researchers have been trying to understand which brand content results in more comments, likes and shares but have not considered the potential mediating role of different social media. This is an important question to regard, as recent research agendas point out to the heterogeneity effect of social media design on relationship formation among individuals and companies (Aral *et al.*, 2013; Schultz and Peltier, 2013).

Companies use virtual social media to enhance interaction with their current and potential customers by publishing posts. Posts use publications features such as text, photos, and videos, which can facilitate interaction among users (De Vries *et al.*, 2012). Usually, empirical research focusses on post typology effects on Facebook, but companies are also using Instagram. Launched in 2010 and designed only for smartphones, the aim of the platform is to share photos and videos (up to 15 seconds) freely. The resulting popularity disseminated to business and 65 percent of the world leading brands have already an account on the platform (Statista, 2013). Not only big brands have been using Instagram. Small business found a cheap way to promote and sell their products, especially the fashion industry, such as clothing and accessories (*Forbes*, 2013), and this must be taken into consideration by researchers.

We organize the paper as follows. First, we briefly present metrics for interaction on the most popular virtual social media. Next, we outline the research background on of post typology and provide the basis for hypotheses construction. Research method and results are provided after the hypotheses, and we conclude our paper with research and managerial contributions and limitations.

Virtual social media and metrics for interaction

Social media are important forms of virtual communications in which participants share information, knowledge, and maintain social ties (Boyd and Ellison, 2007; Ellison *et al.*, 2007). They are defined as spaces where users create profiles, articulate themselves, and interact in different levels with other people, brands, and companies (Boyd and Ellison, 2007). Over the last years social media such as Facebook and Instagram have put together millions of members. The last estimation indicate 1.49 billion active users on Facebook and 300 million users on Instagram (Facebook, 2015).

This popularity seems to span different cultures. According to a social media monitoring service SocialBakers, a posting referring to a release of a new Taco Bell product onto the US market yielded 360,606 interactions (322,973 likes, 12,302 comments, 25,331 shares) (SocialBakers, 2015b) in just one month, while in Brazil a similar posting about the release of a new footwear resulted in 353,321 interactions (341,392 likes, 7,688 comments, 4,241 shares) (SocialBakers, 2015a). Given the importance of virtual social media to interaction between companies or brands and potential consumers, scientific researchers have been published about different issues.

One specific topic highlights the impact of different types of content on social media metrics. There are numerous social media metrics as pointed out by Peters *et al.* (2013) and there is a controversy regarding the choice on the use of appropriate indicators. Apart from the discussion on the usefulness of each metric to reflect business reality, a common ground for the research on this field is to use data from social media to understand the variation on non-economic variables, such likes, comments and shares (Luarn *et al.*, 2015).

Usually, social media authorize the creation of individual and company/brand profiles which are used as interaction tools. Users can incorporate personal and professional information, upload photos and invite friends, while brands can connect to their consumers and publicize marketing related material (Boyd and Ellison, 2007; Smith *et al.*, 2012). After creating profiles to communicate to consumers, companies, and brands incorporate contents such as news, photos, and videos, seeking to raise visitor levels and the aforementioned metrics. The five most popular virtual social media and their characteristics and metrics are shown in Table I.

Research background on post typology in single social media

Literature on the impact of companies posts typology is growing rapidly in the last five years, but usually concentrate on semantic (text content) or richness (moving-pictures that complement text, such as pictures and videos). Some studies analyze the number of media elements or media type (text, photo, or video) and the presumable positive impact in consumer responses, such as comments, likes, and shares (Kim *et al.*, 2015; Rauschnabel *et al.*, 2012).

Another group classifies post types and media elements such as richness of content and results indicate that images and videos are responsible for a positive influence on likes and comments (De Vries *et al.*, 2012; Sabate *et al.*, 2014). One last group includes the brand effect and text content as independent variables and results show that avoiding hard sell types could increase the number of likes inasmuch as including corporate brand names and emotional tones in Facebook posts (Swani *et al.*, 2013).

Results on the impact of text content is controversial: some studies found that contents such as entertainment and information raises, on average, the number of likes, comments, and shares (Cvijikj and Michahelles, 2013) while others not (De Vries *et al.*, 2012). From all the recent empirical research conducted, one may conclude that extant research classifies post typologies in different forms and do not consider potential differences across social media, since empirical efforts concentrate on Facebook.

Media characteristics can shape individual objectives and experiences in virtual environments (Hoffman and Novak, 1996) and new studies are stressing the mediating

Virtual social media	Primary metrics	Specific characteristics
Facebook	Comments Likes Shares	Creation of groups, pages, events and advertisements Use of applications Add more than one user to a conversation
Instagram	Comments Likes	Postings originated exclusively from smartphones and tablets Postings with images and short videos (up to 15 seconds) Editing images and videos tool
LinkedIn	Comments Likes Shares	Relationships based on professional contacts Profiles containing professional information Participation in groups
Twitter	Favouriting a tweet Likes Incorporate a tweet (quoting) Retweet (share)	Personal or professional messages with a maximum of 140 characters
YouTube	Didn't like Likes Shares	Creation and interaction with personal or third-parties videos Enroll in content channels

Table I. Characteristics and metrics for engagement in the most known virtual social media role that different social media has on user interaction. Instagram, for example, poses singular forms of engagement because alters temporal and vertical structures in favor of spatial connectivity's. Based on photo sharing, this social media requires a specific device (a smartphone) and exhibit a dynamic timestamp, "as each image shows a constantly changing representation of time" (Hochman and Manovich, 2013).

Our empirical study incorporates these differences as it considers brand typologies as a source of interaction, but contemplates the potential mediating role of social media. Research design followed previous procedures of categorizing post typology of business from different segments. However, the selection criteria included one additional component, since the companies studied were active on the two most popular social media sites, Facebook and Instagram. Table II illustrates the current literature on post typology effects and the research gap addressed by our study.

Method

Our research is characterized by being causal look through quasi-experiment procedures, establish relations of cause and effect between the independent and dependent variables (Malhotra and Birks, 2007). The empirical study took place in a quasi-experiment or econometric treatment since both the choice of the companies as of the posts was not carried out by random assignment (Shadish *et al.*, 2002). To perform the data collection was selected five companies accessible to researchers to: ensure the small business profile; and assess the free advertising of products and service offers by small businesses on Instagram. The selection of companies obeyed the following criteria: different segments; active accounts on Facebook and Instagram; at least three weekly posts as each social network analyzed.

The segments of the chosen companies were the food, beauty, women's shoes, fashion design, and body fitness. The operationalization of the research took place after the collection and categorization of publications of 1849 posts (680 on Facebook and 1,169 on Instagram) of the chosen companies. The purpose of this choice was to reproduce user interaction with different groups and social media. Posts refer to the period between January and August of 2014. These choices differ from previous research. De Vries *et al.* (2012) evaluated the food segments, accessories, leisure wear, alcoholic beverages, cosmetics, mobile phones, and brought together 355 posts, while Swani *et al.* (2013) collected 1,143 observations, both only on Facebook.

Study procedures and variable

Data collection was carried out on Facebook and Instagram of each company during the months of August and September of 2014 through a browser feature that lets you save all the page data. This procedure enables all contents to be saved for the extent that the page has loaded, storing the data onto HTML file extension. The data

Description	References
Single social media with multiple brand or companies of one sector	Rauschnabel *et al.* (2012) and Sabate *et al.* (2014)
Single social media with multiple brand or companies of various sectors	Cvijikj and Michahelles (2013), de Vries *et al.* (2012), Kim *et al.* (2015) and Swani *et al.* (2013)
Multiple brand or companies of various sectors across social media	Our empirical study

Table II.
Current literature on post typology effects

contained the variables of interest (type of posts), control (segment week period in which the posting, month, and the text of the post) and dependent (like and comments) empirical models. These data were then systematized in a spreadsheet Excel software to be analyzed using Stata software (version 13.1). The data were arranged in cross-section since they were not collected information on the posts of time.

The categorization of types of threads extended previous research carried out in the context of Facebook and was operationalized with a typology that considered the content of messages posted on the social network. This categorization occurred after analysis of investigations into similar objectives. Caseiro and Barbosa (2011) classified the threads into three groups (advertising/services/campaign information and offers/contests/hobbies). Rauschnabel *et al.* (2012) limited to classify posts according to technical characteristics such as size, an amount of text, media elements (such as pictures) and the presence of polls. De Vries *et al.* (2012) used six types, but with other features in addition to the content, such as posting the location on the page. The work of De Vries *et al.* (2012) appealed to four specific types: interactive, informative, entertaining, and contrasting content. Smith *et al.* (2012) built six categories and compared to platforms Facebook, Twitter, and YouTube, while Swani *et al.* (2013) identified three types, based on psychological model choice Hansen (1976). The categorization of Swani *et al.* (2013) classified the postings: those who use business names, which refer to emotional content and that references to make instant purchases of products or services.

The classification proposed to this paper is a quantitative improvement on the mentioned studies and feature posts into five categories: advertising, events, fan, information, and promotion. Table III presents and describes the variables of interest in the study: the dependent variables, which are in a quantitative way, and the independent variables in the qualitative form.

With the proposed categories of threads supported by Facebook and Instagram, it was proposed five hypotheses to be evaluated in the study. As in the study of

Variable	Description	Nature	Notation
Likes	Quantity of likes received per post	Dependent/ Quantitative	LIKE
Comments	Quantity of comments received per post	Dependent/ Quantitative	COM
Advertising	Posts to promote brands in social media present publicity items which cross the digital sphere and posts with entertaining content, to attract the attention of their followers and acquire larger numbers of likes and comments	Independent/ Qualitative	ADV
Fan	A fan is responsible for the main idea of post, or for sending the photo. Their participation is always mentioned in the post	Independent/ Qualitative	FAN
Events	Posts, with photo and video media, directly connected to brands or otherwise	Independent/ Qualitative	EVE
Information	Content with data about events, places, opportunities, people, or celebrities, directly connected to a brand or otherwise	Independent/ Qualitative	INFO
Promotion	Posts with quizzes, which promote participation of followers through rewards	Independent/ Qualitative	PROM

Table III.
Interest variables of the empirical study

De Vries *et al.* (2012), we assume that the posting category has a positive relationship of the dependent variables (interactions) choose:

H1. Posts of advertising category have a positive relationship with the interaction of posting.

H2. Posts of the events category have a positive relationship with the interaction of posting.

H3. Posts of fan category have a positive relationship with the interaction of posting.

H4. Posts of information category have a positive relationship with the interaction of posting.

H5. Posts of promotion category have a positive relationship with the interaction of posting.

Additionally, our study found that there are five control variables against three of the work of De Vries *et al.* (2012) and only two in the search Swani *et al.* (2013). First, the business segment was controlled from the collection posts of five different segments profiles, such as the research De Vries *et al.* (2012), who used as a control variable product categories. The study also relied on De Vries *et al.* (2012) to assign as a control variable for the week period in which the posting (weekday or weekend). The other variables had to evaluate the seasonality of posting (month) and the characteristics of the text used in the posting of the description (number of characters and the use of tagging). The evaluation of the use of tagging on social network was previously used in the study of Nam and Kannan (2014). In the survey the tagging was seen as "new way to share and online categorize content that enables user to their express thoughts, perceptions, and feelings with respect to diverse concepts," lining up with the interest of our research in evaluating text features that can influence threads. Table IV presents and characterizes the study of the control variables.

We built two econometric models to evaluate each social network in which the dependent variables are, respectively, like and comments. The models incorporate quantitative and qualitative independent variables discussed in Tables III and IV. The representations of the parameters and intercept of the models are reproduced in Equations (1) and (2). The estimation was performed using the method of ordinary

Variable	Description	Nature	Notation
Companies segments	Food (restaurants), beauty (hairdressing), ladies' footwear, body design (tattoos), fashion gym wear (women's fashion gym wear)	Control/ Qualitative	FOOD, HAIR, FOOT, DES, FASH
Week period	Posts that occurred in the middle of the week (between Monday and Thursday) or the weekend (Friday, Saturday or Sunday)	Control/ Qualitative	WDAY, WEND
Month of the post	Posts of months January, February, March, April, May, June, July, and August	Control/ Qualitative	JAN, FEB, MAR, APR, MAY, JUN, JUL, AUG
Number of characters	Number of characters used in the description of the post	Control/ Quantitative	CHAR
Tagging	Word or phrase after the sign in the description of the post (#)	Control/ Qualitative	TAG

Table IV. Control variables of the empirical study least squares. This method estimates the parameters of the sample regression function so that the sum of residuals is as low as possible and in which the estimated values are the closest possible observed values (Greene, 2012). The dependent variables (like and comments) and independent with quantitative trait (characters) were transformed to logarithm notation, as well as in the study by De Vries *et al.* (2012) to facilitate comparison of results.

Equations (1) and (2) follows:

$$\begin{aligned}\text{like} = {} & \beta_0+\beta_1 adv+\beta_2 fan+\beta_3 eve+\beta_4 info+\beta_5 ser+\beta_6 prom\\ & +\beta_7 food+\beta_8 hair+\beta_9 foot+\beta_{10} des+\beta_{11} fas+\beta_{12} wday\\ & +\beta_{13} wend+\beta_{14} jan+\beta_{15} feb+\beta_{16} mar+\beta_{17} apr+\beta_{18} may\\ & +\beta_{19} jun+\beta_{20} jul+\beta_{21} aug+\beta_{22} char+\beta_{23} has+\mu \end{aligned} \tag{1}$$

$$\begin{aligned}\text{comments} = {} & \beta_0+\beta_1 adv+\beta_2 fan+\beta_3 eve+\beta_4 info+\beta_5 ser\\ & +\beta_6 prom+\beta_7 food+\beta_8 hair+\beta_9 foot+\beta_{10} des\\ & +\beta_{11} fas+\beta_{12} wday+\beta_{13} wend+\beta_{14} jan+\beta_{15} feb\\ & +\beta_{16} mar+\beta_{17} apr+\beta_{18} may+\beta_{19} jun+\beta_{20} jul\\ & +\beta_{21} aug+\beta_{22} char+\beta_{23} has+\mu \end{aligned} \tag{2}$$

Data analysis

Descriptive statistics

In Table V, is the summary of the dependent variables used in the econometric models and the number of posts collected by segment. Like it is observed that has the highest average among the variables. Instagram also has a higher average (like 4,210 and 69,686 comments) compared to Facebook (23,764 like and 1,091 comments). These results suggest that the interaction between customer and company on Instagram is more common, perhaps the unique interactions via smartphone and have the characteristic of posting photos or videos. Another reason is the increased time spent by users on the smartphone. Among the Americans, for example, the time from 40 minutes a day in 2010 to 134 minutes in 2014 (Statista, 2015). It is observed that like

Social media	Variables	Observations	Average	SD	Minimum	Maximum
Facebook	LIKE	680	23.764	54.907	0	1037
	COM	680	1.091	3.523	0	32
Instagram	LIKE	1.169	69.686	60.288	6	362
	COM	1.169	4.210	12.009	0	286
Business segments		Facebook			Instagram	
	M (like)	*M* (comments)	Posts (*n*)	*M* (like)	*M* (comments)	Posts (*n*)
Food	75	3	78	57	5	53
Beauty	3	0	122	30	3	418
Ladies footwear	1	0	2	33	4	148
Body design	113	7	45	201	8	104
Fashion gym wear	11	0	433	90	5	446

Notes: *M*, mean of business segments by post; *n*, total number of posts

Table V. Descriptive statistics of the dependent variables and posts by business segments has the highest average among the segments. On the contrary, reviews have the lowest average frequency between the two dependent variables. A likely reason for this result is that individuals spend more effort in writing comments on posts on social networks. Comments also appear as lower standard deviation variable, revealing lower dispersion of data. It should be noted that: the maximum values of variables follow the same layout: first, like (1,037 on Facebook and 362 on Instagram), followed by shares (32 on Facebook and 286 in Instagram); and the body design segment has the highest average of the dependent variables in the two social networks.

Specification tests, F-test and quality adjustment models

As a first step in the analysis, specification tests were performed and read from the multiple linear constraints tests (test *F*) and the results of determination of the coefficients of the models (R^2 and adjust R^2). Table VI presents the estimates of the

	Facebook		Instagram	
	Model 1 – like	Model 2 – comments	Model 1 – Like	Model 2 – comments
Variables of interest				
Post typology				
adv	0.2948 (1.08)	****	0.1884 (1.24)***	−0.1459 (−0.44)
fan	0.2287 (0.83)	−0.3276 (−0.59)	0.0280 (0.18)	−0.0672 (−0.20)
eve	−0.2742 (−0.88)**	−0.0066 (−0.01)	0.3437 (2.07)*	−0.5745 (−1.57)***
info	0.2483 (0.86)	−0.1572 (−0.25)	−0.2085 (−1.30)	−0.2780 (−0.80)
prom	0.1393 (0.47)	****	0.1715 (0.93)*	0.5236 (1.33)***
Control variables				
Segments				
food	2.0031 (3.63)***	0.6657 (1.50)	−0.3456 (−4.30)***	0.4482 (2.48)**
hair	−0.7182 (−1.30)	****	−0.9983 (−16.54)***	−0.0961 (−0.68)
foot	−1.1274 (1.67)	****	−0.8026 (−11.74)***	0.4781 (3.10)**
des	2.4400 (4.42)***	1.3220 (2.83)	0.8510 (16.57)***	0.8482 (7.70)***
Week period				
wday	−0.079 (−0.15)	0.0360 (0.21)	−0.034 (−1.22)	0.09888 (1.51)
Month post				
jan	0.7330 (−5.02)***	−1.0651 (−2.47)	−0.0061 (−0.10)	0.05736 (0.42)
feb	−0.5959 (−3.89)***	−1.3132 (−3.02)	−0.0025 (−0.05)	0.2434 (2.06)*
mar	0.5628 (−3.71)***	−1.5776 (−3.48)	0.1323 (2.46)*	0.5247 (4.23)***
apr	−0.2237 (−1.60)	−0.8824 (−2.15)	0.1694 (3.42)**	0.2941 (2.52)**
may	−0.2144 (−1.49)	−0.8902 (−2.18)	0.1746 (3.49)**	0.1164 (0.98)
jun	−0.3468 (−2.41)**	−1.02555 (−2.41)	0.2344 (4.92)***	0.1967 (1.75)
jul	−0.3363 (−2.25)*	−0.8379 (−1.95)	0.0657 (1.36)	0.2543 (2.20)*
Text post				
carac	0.8063 (3.69)***	0.1724 (2.87)	0.0061 (0.63)	0.1177 (4.83)***
tag	0.2634 (0.48)	−0.0249 (−0.05)	0.1551 (2.91)*	0.2141 (1.74)
Constant	1.74 (2.78)	0.67 (0.77)	4.00 (22.54)	0.29 (0.75)
F	108.61***	4.80***	166.43***	13.49***
R^2	0.7599	0.3371	0.7337	0.2240
Adjust R^2	0.7529	0.2669	0.7292	0.2074
Number of obs	680	680	1.169	1.169

Notes: The *t*-statistics are in parentheses, located below the estimates of the variables of interest and control. *Significant differences ($p < 0.05$); **Very significant signal values ($p < 0.01$); ***Highly significant values ($p < 0.001$); ****Omitted because present collinearity

Table VI. Results of the estimates of the coefficients and statistics of the two models constructed for each social media models for social network operationalized with robust procedures about heteroscedasticity. Wooldridge (2013) indicates that estimator's variances are biased without the possibility of homoscedasticity; as a result, inadequate inferences are conducted in the presence of heteroscedasticity (White, 1980). The identification of this feature happened after performing the Breusch and Pagan (1979) test, which returned high values of the χ^2 statistic and allowed reject the null hypothesis of constant variance (Chi = 3138.87 in Model 1; qui = 1616.39 in Model 2 on Facebook, qui = 621.68 in Model 1, qui = 27138.47 in Model 2 on Instagram). Another test identified values of the variance inflation factor (VIF) models. Gujarati and Porter (2011, p. 337) argue that this factor "shows how the variance of an estimator is inflated by the presence of multicollinearity." The values returned by the tests indicate VIF average closer to the value 1 and away from 10, which indicates the existence of an acceptable collinearity between the independent variables (average VIF equal to 1.32 to Facebook and average equal to 1.73 for Instagram).

It is necessary to highlight the organization procedure of data and allocation of reference categories in qualitative variables so that they properly interpret Table VI. As a general principle to include dummy variables that indicate different groups in the case of regression model shows "g" groups or categories, there is the need to include the g – one variables in the models (Wooldridge, 2013). The reference variables defined in both models for social media Facebook and Instagram were: "prom" for posting typology group, "fash" for the enterprise segment, "wend" for the week period and "aug" for month post. This grouping was selected, after conducting several tests between variables, for the following reason: this combination results in intercepts that are not statistically significant, allowing appropriate comparisons between the intercepts groups of dummy variables to intercept the group base (Wooldridge, 2013). The no statistical significance guarantees the constant comparisons between the posting types of coefficients when they are significant.

Model 1 returned in the two largest social media values of R^2, which measures the proportion of total variation in the dependent variable explained by the regression model (Gujarati and Porter, 2011; Wooldridge, 2013). When comparing the determination coefficients of the models presented in this work with marketing researches conducted in the context of social media, it is observed that are superior: the study by De Vries *et al.* (2012) in the context of Facebook, the results were 15 percent in the like model and 30 percent in the comment model against 75.18 and 27 percent, respectively on Facebook and 73 and 20 percent in Instagram. An argument should be put on the agenda on this issue, this paper advances in understanding the impact of the type of posting by considering additional shares as the dependent variable.

The models for number of like and comments are jointly statistically significant. The test F-values allow reject the null hypothesis that the slope coefficients are simultaneously equal to 0 (Gujarati and Porter, 2011). The R^2 values and adjust R^2 explain the variance of the dependent variables in a reasonable way for Models 1 ($F = 108.61$ value, p-value < 0.01, $R^2 = 75.99$ percent and adjust $R^2 = 75.29$ percent on Facebook and value $F = 166.43$, p-value < 0.01, $R^2 = 73.37$ percent and adjust $R^2 = 72.92$ percent in Instagram) and 2 (F-value $= 4.80$ $p < 0{:}01$, $R^2 = 33.71$ percent and adjust $R^2 = 26.69$ percent on Facebook and value $F = 13{:}49$, p-value < 0.01, $R^2 = 22.40$ percent and adjust $R^2 = 20, 74$ percent in Instagram).

Analysis of the impact of the variables of interest

The second stage of analysis involved the results of hypothesis tests on the individual estimates of the regression coefficients. Two important considerations about the variables of interest should be highlighted: the types of posts that impact like and comments are different in the analyzed social media, indicating a theoretical and empirical way for future work aimed at classifying and identify the influence of these types in different virtual social networks; and the event category is the one that has an impact on Facebook (like) and Instagram (like and comments), which indicates a typology for digital content managers consider during the planning of posts that will be posted on social networks like Instagram and Facebook.

Category advertising posts are statistically significant at a confidence level of 99.9 percent in the like on an Instagram model and is characterized by linear, positive impact on the dependent variable like. A post published with the kind of advertising in a business segment receives 18.84 percent more like than posts of fan categories, event, information, and promotion, the latter category of reference. Unlike threads promotional type, characterized as advertising are not linked to contests, sweepstakes or rewards and are designed to promote the brand, sometimes referring to festive dates like Christmas. The statistical significance of this type appears to be related to brand management in the post-internet reality process: it is a more dynamic context that seeks to involve consumers at key stages of the process of brand building (Christodoulides, 2009).

The second type of posts that promotes linear impact on like on Facebook and like and comments on Instagram is the event. However, the results of this category are slightly less consistent in econometric terms: they are significant at a level of 95 percent to like on Facebook and 90 to 99.9 percent and like for comments on Instagram. The event posting receives 27 percent of like on Facebook. For Winer (2009), virtual social networks like Facebook are equipped with features that enable companies to communicate with specific segments and engage individuals through interactivity. One of those ways would be to invite the followers for events organized by companies. However, as the create feature events can be used between users and between company and followers, the feature does not arouse positive intention of followers enjoy posting on Facebook. Instagram on the event type has two different behaviors. Increases by 34 percent the number of like, but reduces the number of comments on 57 percent. This behavior can occur by the user's ease interacting with the post only with the like, not producing a text or informing another user in the comments as a way to publicize the event.

The promotion typology promotes linear and positive impact on the dependent variables only on Instagram. At a 90 percent confidence level posts receive promotional 17.15 percent more like than threads categories of services. About comments and a 99.9 percent confidence level, the typology receives 52.36 percent more comments. Promotional activities may go beyond the immediate effect on sales and influence consumer learning and their behavior in the long run (Van Heerde and Neslin, 2008). It seems to be the goal of companies when they encourage some activity follower in their profiles in exchange for participation in sweepstakes and contests. These mechanisms also part of the scope of promotional activities, although the goal is no effect on sales or profitability, the behaviors and attitudes of individuals (Chandon, 1995). In this sense, an important managerial implication refers to the use by marketers, postings characterized as promotional.

The other two types of posts analyzed (fan and information) does not promote statistically different impacts of the reference variable (promotion). These results together early indications of no significance of these typologies and additional studies are needed to identify the recurrence of this pattern with companies in other industries. Specifically dealing on informative posts, literature had already given evidence of no statistical significance in that category. De Vries *et al.* (2012) did not fail to reject the hypothesis that informative posts and comments get more like than those characterized as non-informative. The decision to include it in the group of five variables of interest was due to the need to test a broader group of typologies that De Vries *et al.* (2012) and Swani *et al.* (2013) (Table VII).

Analyzing the impact of control variables

The first set of control variables refers to enterprise segments. The variable qualitative reference was chosen gym fashion segment wear and according to the results, it is apparent that only the feed body segments and drawing are statistically significant in the two studied social networks. Posts on meal segment increase like on Facebook at 200.31 percent, representing a decrease of 34.56 percent on Instagram while comments have an increase of 44.82 percent over the gym fashion wear segment. Instagram on the hair segment has a fall of 99.83 percent in the number of like to a confidence level of 99.99 percent. The foot segment has a linear impact on Instagram with a decrease of 80.26 percent in the number of like and an increase of 47.81 shares. As well as the power segment, the body design influences Facebook and Instagram. There is an increase in the number of like Facebook (244 percent) and like (85 percent) and comments (84.82 percent) on Instagram. Especially the increase of interaction in the power segment when they are posted photos of desserts, and photos in the body design firm present the new tattoo will be made on a consumer. Both the photo of dessert as the body design that will be done, characteristics were present in the posts with the most like and comments.

Posts published during the week are statistically the same as the weekend. This means that do not cause impacts on reviews and like. These results corroborate what was found in the study by De Vries *et al.* (2012), which also included days of the week as a control variable and did not find statistically significant results. That way, you can ensure that users like, share and comment threads with equal frequency on weekdays and weekends and make use of Facebook and Instagram in different ways that e-mail services, for example. Another variable about post, month, showed different behaviors. Facebook, the month of January and March, had a positive impact while the months of February, March and June had a negative impact, and Instagram returned different results on the models evaluated, but all positive. In the case of like, the months of March, April, May, and June showed an average increase of 17.76 percent and comments the increase occurred in February, March, April, and July. In particular, the increase in the number of like from February and March is explained to represent a period of national holidays in the country of the companies surveyed, and July a vacation, which tends to increase the release of stocks of companies with their followers.

The third control group of variables analyzed characteristics the type of text of posts. Regarding the like Facebook, the number of characters representing an increase of 80.63 percent. As for the Instagram, only comments have a positive linear impact on the number of characters of the post. This behavior can be caused by the preference of

Table VII.
Summary of results

		Likes		Comments	
Post typology	Expectation	Instagram	Facebook	Instagram	Facebook
H_1: advertising	+	Supported	Unsupported	Unsupported	Unsupported
H_2: event	+	Supported	Supported	Supported	Unsupported
H_3: fan	+	Unsupported	Unsupported	Unsupported	Unsupported
H_4: information	+	Unsupported	Unsupported	Unsupported	Unsupported
H_5: promotion	+	Supported	Unsupported	Supported	Unsupported

consumers interact with posts that have not only photos and informative text. The Instagram like model returned to a significant 90 percent, an increase of 15:51 percent in posts that have tags, a common feature in threads companies in Instagram, by posting describing the characteristics using different tags.

Conclusions and further research

This study aimed to measure the impact of the posting on important metrics in two social medias. Event postings exert a linear impact on the dependent variable of the analyzed social medias, suggesting a standard, and indicates a theoretical and empirical way for future studies directed to classify and identify the influence of this type. We conclude that virtual social medias like Facebook and Instagram are more efficiently utilized when used as a means of promotion that provides hedonic benefits to users, rather than commercial benefits through direct promotion of products, services, and prices (Chandon, 1995; Chandon *et al.*, 2000). The types that were statistically significant possibly promote it Subramani and Rajagopalan (2003) classified as emotional engagement and connection of individuals with the transmitted message. This connection allows the diffusion of posting to social media friends in the social circle.

Future investigations should proceed from the model presented in this work and analyze, for example, the dependent variables as members of simultaneous equations or a system in which the terms of disorder are highly correlated (Zellner, 1962). Exploratory analyzes with the database of this research show that the coefficient of determination increases significantly when including shares and like as independent variables Models 1 and 2. Understanding this dynamic is important since there seems to be a relationship between the dependent variables: individuals who enjoy a particular post, also seem to comment on it and share it.

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