Finding the optimal social media marketing mix to drive customer attraction and sales performance: an exploratory study

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Abstract: Prior studies confirm the influence of social media marketing on a variety of psychological dimensions. However, without tangible performance metrics, most of these studies have been unable to directly and conclusively measure the effectiveness of social media strategy. Utilising data from the 500 largest internet retailers in the USA, this study explores the relationship between social media marketing, customer attraction and sales performance. The results of our research show that the optimal combination of social media outcomes for enhancing customer attraction includes maximising the number of likes for Facebook, the number of followers for Twitter, and the number of views for YouTube. To improve sales performance, the optimal approach includes maximising the number of likes for Facebook and the number of followers for Twitter. Further findings reveal that customer attraction mediates the relationship between social media marketing and web sales.

Keywords: social media marketing; SMM; customer attraction; web sales; Facebook; Instagram; Pinterest; Twitter; YouTube.

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1 Introduction

Social media has changed the way information is created and consumed. Just as quickly as they can absorb information, consumers can also "become a source of information to which others can subscribe and the content of which others can collectively filter, authenticate, and verify" [Clemons et al., (2017), p.431]. Approximately two-thirds of online adults use social media platforms. In the USA, a typical individual participates in online leisure activities, including social media, for about 1.5 hours per day on weekdays and 2.33 hours per day on weekends (Dong et al., 2018). Thus, social media has become an integral part of consumers' daily activities. From a business perspective, organisations view this social media engagement as a window of opportunity, and most marketers are keen to explore different ways to capitalise on its potential. As such, organisations are increasingly investing in new marketing channels, leveraging technologies, and building their brands through social media-based shopping, social-media-driven customer support and viral marketing (Kumar et al., 2013; Constantinides et al., 2015). Accordingly, social media platforms such as Facebook, Instagram, Pinterest, Twitter and YouTube have taken on a primary role in the promotional programs of online retailers.

The academic literature is replete with social media focused studies examining issues such as purchase intentions (Erkan and Evans, 2018; Yeo et al., 2020), customer relationship management (Nigthoujam et al., 2020; Trainor et al., 2014) and brand management (Asmussen et al., 2013). Another popular research stream is dedicated to online customer reviews, including the information processing and psychological routines of participants (Liu and Karahanna, 2017; Siering and Janze, 2019).

While these studies confirm the influence of social media on a variety of psychological dimensions, most of them have been unable to directly and conclusively measure the effectiveness of social media strategy using tangible performance metrics. It is unfortunate, as many practitioners are understandably turning their attention to questions regarding the return on investment (ROI) of social media. They urge that understanding the impact of social media marketing (SMM) efforts in monetary terms is necessary to help develop optimal marketing strategies (Agostino and Sidorova, 2016). Thus, the question remains: does SMM lead to significant attraction to a marketer's transactional website, and ultimately, more sales?

Consistent with recent research trends in the field (e.g., Felix et al., 2017), this study makes the following contributions to the domain. First, rather than considering a single social media platform, we take a holistic approach by examining a combination of social media sites. We also evaluate the impact of SMM from multiple perspectives. These include the behavioural perspective (customer attraction to a particular website) and the financial perspective (the direct measurement of web sales). We begin by presenting the literature review, where we draw attention to the gaps in the research stream and the ways to address those deficiencies. The subsequent sections describe the dataset, the measurement of the research variables, and the statistical approach used to test the hypotheses. Finally, the findings, along with discussion and implications, are presented.

2 Literature review

Social media can be defined as a group of internet-based applications that allow for the creation and exchange of user-generated content (Kaplan and Haenlein, 2010; Wang et al., 2017). Although social media are generally referred to and discussed as a collective entity, in reality, 'social media' is a broad label that applies to several different types and styles of media channels, each with its own unique capabilities and user demographics. One simple typology of social media is to distinguish between social network sites (Facebook), picture-sharing sites (Instagram), scrapbooking sites (Pinterest), blog and micro-blog sites (Twitter) and video-sharing sites (YouTube) (Mills and Plangger, 2015). Most commonly, organisations use social media to interact with highly dispersed customers online, form communities that interactively communicate, build brand credibility and reputation, and become part of customer conversations (Felix et al., 2017). Social media has not only changed the way that organisations interact with their customers, but the very nature of business itself.

The theoretical framework that can help explain the impact of social media on consumer behaviour is provided by social legitimacy theory. According to social legitimacy theory, people are often motivated by the perception that a particular action is desirable, proper, or appropriate as determined by a socially constructed system of norms, values and beliefs (Suchman, 1995). Within the past decade, researchers have applied the concept of social legitimacy with the purpose of addressing why consumers perceive certain brands or consumption practices as acceptable, but not others (Humphreys and Latour, 2013). In fact, the communication of social norms and expectations can be considered one of the most significant determinants of a company's success in the marketplace. Moreover, a wide range of media, communications methods, and authorities can be used as bases for these social legitimacy judgments. In the contemporary business climate, social media may be the primary mechanism responsible for the social legitimisation of the firm (Hakala et al., 2017).

Consequently, organisations no longer view social media as a consumer fad. Instead, they increasingly consider it to be an integral part of their marketing mix. As such, they have begun to manage it in the same manner as their traditional media activities (Peters et al., 2013). For example, firms have adopted social media for various marketing activities such as branding, market research, customer relationship management, service provision and sales promotion (Helena et al., 2016). Broadly speaking, SMM refers to how firms use a combination of different social media elements to create value for their users (Felix et al., 2017). Empirical research studies examining SMM note that it has important implications for a firm's marketing performance, including increasing brand awareness, generating traffic to online platforms, and reducing overall marketing costs (Ashley and Tuten, 2015; Bianchi and Andrews, 2015; Ford, 2019).

Unfortunately, the majority of the extant studies examining SMM constrict their approach by focusing on the usage of social media by technology-based firms or on measuring the ROI for specific SMM campaigns (Helena et al., 2016). Also, many studies concentrate on consumer perspectives, such as the underlying motivation to use social media or the various methods that work to socially engage the consumer (Hoffman and Fodor, 2010). A key finding in this area is that social media contribute to increased consumer interest and purchase intentions for a wide range of products (Alhabash et al., 2015).

On the other hand, studies focusing on firm-level perspectives and overall business performance tend to be less frequent. One reason for this research gap is because manipulating behavioural data at the individual level can be unmanageable in a marketplace with millions of users (Ayanso and Yoogalingam, 2009; Gudigantala et al., 2016). Nevertheless, the underlying assumption is that social media can generate increased sales and ROI (Kumar et al., 2013).

Studies have proposed several measures to model ROI in the social media context (Fisher, 2009; Zhao and Zhu, 2010). Yet, there are some significant concerns. For instance, ROI is typically assessed through proxy variables. For example, as a proxy for sales performance, many of the prior e-commerce studies have used website satisfaction (Kim et al., 2008; Limayem et al., 2000). This approach often involves exploring the factors likely to drive satisfaction, such as ease of navigation, speed of the website, compelling product descriptions, and overall trust in the website (Gudigantala et al., 2016). However, there is no conclusive empirical evidence that website satisfaction leads to an increase in sales performance (Ayanso and Yoogalingam, 2009).

Another critical weakness of many e-commerce studies focusing on SMM is that very few studies analyse a wide range of distinctive social media platforms. Instead, the vast majority of studies tend to centre solely on Facebook, the most widely adopted social media network (Helena et al., 2016). Given its prominence, it is not surprising that Facebook is widely viewed as the most efficient platform for social endorsement and opinion leadership (Anspach, 2017). Nevertheless, a detailed analysis of SMM must include a representative sample from a variety of unique platforms. In addition to Facebook, this should consist of the other distinctive platforms outlined by Mills and Plangger (2015): Instagram, Pinterest, Twitter and YouTube.

Launched in 2010, and purchased by Facebook in 2012, Instagram is a photo/visual-based social media platform. In recent years, Instagram has enjoyed a rapid rise in popularity. As a site optimised for self-presentation, Instagram facilitates information sharing and social interaction (Phua et al., 2017). Similarly, Pinterest is another social media site that has been attracting the attention of advertisers in recent years. The primary focus of Pinterest is on discovering, archiving, and sharing visual images, allowing users to share their interests or lifestyles with like-minded others. Many Pinterest users facilitate brand interactions by pinning or repinning branded images, which can have a positive impact on consumer purchases (Youn and Jin, 2017). In recent years, Twitter has become a popular online social network in which users publicly communicate short messages to followers. Research shows that popularity alone, based on the number of followers, is an excellent predictor of Twitter's social influence (Phua et al., 2017). Finally, YouTube is an attractive platform for creating and posting video content that can be shared almost instantaneously with a worldwide audience. YouTube users can subscribe to channels, comment on or choose favourite videos and even post responses to other channels, making it an ideal platform for enabling social interactions and disseminating digital social influence.

3 Hypotheses

Consistent with Mills and Plangger (2015), the current study proposes a holistic approach to the study of social media that considers the broad construct of SMM. In the current business environment, SMM efforts will typically encompass the coordinated use of Facebook, Instagram, Pinterest, Twitter and YouTube. Moreover, this study overcomes the existing limitations of prior research studies addressing outcome measures by considering the dependent variable from both behavioural and financial perspectives.

Although popular among researchers, using proxy measures for business performance tends to be ambiguous. According to Hoffman and Fodor (2010), proxy measures often yield inconclusive results. Instead, using direct measures and hard numbers, such as web sales, is crucial as they represent the ultimate manifestation of customer motivations. In addition, we examine the interrelationship between customer attraction to the website and web sales. Examining the influence of customer attraction is consistent with other studies that have used it to compute conversion rate and have argued for its prevalence (e.g., Ayanso and Yoogalingam, 2009; Gudigantala et al., 2016). Based on the arguments presented above, we posit three sets of hypotheses related to: direct customer attraction, direct web sales and mediation effects (SMM × customer attraction).

H1a The number of likes on Facebook will have a direct and positive effect on customer attraction.

H1b The number of followers on Instagram will have a direct and positive effect on customer attraction.

H1c The number of followers on Pinterest will have a direct and positive effect on customer attraction.

H1d The number of followers on Twitter will have a direct and positive effect on customer attraction.

H1e The number of views on YouTube will have a direct and positive effect on customer attraction.

H2a The number of likes on Facebook will have a direct and positive effect on web sales performance.

H2b The number of followers on Instagram will have a direct and positive effect on web sales performance.

H2c The number of followers on Pinterest will have a direct and positive effect on web sales performance.

H2d The number of followers on Twitter will have a direct and positive effect on web sales performance.

H2e The number of views on YouTube will have a direct and positive effect on web sales performance.

From a practitioner's standpoint, it should be recognised that efforts to increase customer attraction to a website can be meaningless and even prohibitively expensive if they do not result in increased revenue. Obviously, retailers prefer purchasers to casual visitors, and the focus should not only be on driving visits to a website but on converting visitors to customers once they get there. Since visitors may have different reasons to access a website, it is essential to capture the relationship between visiting and making the actual sale. This leads to the third set of hypotheses as follows:

H3a Customer attraction mediates the effect of number of likes on Facebook to web sales performance.

H3b Customer attraction mediates the effect of number of followers on Instagram to web sales performance.

H3c Customer attraction mediates the effect of number of followers on Pinterest to web sales performance.

H3d Customer attraction mediates the effect of number of followers on Twitter to web sales performance.

H3e Customer attraction mediates the effect of number of views on YouTube to web sales performance.

4 Data

The Internet Retailer's Top 500 Database for the year 2018 served as the sample dataset. This database contains profiles and data on the USA's top 500 e-commerce companies ranked by annual web sales. The database provides a total of 231 metrics for each e-commerce firm, which includes financial, operational, customer service, marketing, corporate information, executive profiles, website performance and vendor information. A systematic process was applied to collect and verify the data. The internal research staff from *Internet Retailer* began by directly contacting each online retailer. Information such as historical knowledge, comparative metrics, expert opinions from technology vendors, and input from market analysts such as *comScore Inc.*, *Experian Marketing Services*, and *ForSee* was used to complete the database. Finally, there was an opportunity given to each retailer to verify the completed metrics. The process yields accurate data, and the validity of the database has led to its use in several previous academic research studies (e.g., Gudigantala et al., 2016; Ranganathan and Grandon, 2002).

The two dependent variables, customer attraction and web sales, were measured using the average number of visits to the website per month and actual web sales. Five social media sites, Facebook, Instagram, Pinterest, Twitter and YouTube, were used to capture the totality of SMM efforts. In addition to their distinctive formats, these five platforms have been rated as among the most popular social media sites based on consumer use (Global Web Index Report, 2019/2020). The number of consumers actively engaged with each of these social media sites was the basis for each platform's metrics. In particular, consumer engagement refers to the number of likes for Facebook, the number of followers for Instagram, Pinterest, and Twitter, and the number of views for YouTube. All of the data collected were in the year 2018. Average ticket (size of the average purchase) served as the control variable. Controlling for the average ticket value enables us to explain the direct effect of each independent variable, negating any possible external influences imposed by the cost of the products purchased. See Table 1 for descriptions of the dependent variables.

Table 1 Description of dependent variables

Variable	*Description*
Customer attraction	A measure of how many consumers visit the website, on average, per month.
Web sales	The retailer's net annual revenue from internet-based transactions.

Several steps were taken to ensure data consistency and accuracy. Since missing values can mislead the estimation process and result in spurious interpretation (Cohen et al., 2003), the first step was to identify those values. This study evaluated five indicators of the broader construct of SMM: Facebook, Instagram, Twitter, Pinterest and YouTube. Therefore, to be included in the analysis, the e-commerce retailer must utilise all five social media platforms. Not only is this stipulation consistent with the SMM construct, but it is also useful in ensuring that there were no confounding effects introduced by different retailer sample sizes for each platform. Accordingly, the decision was to drop the data point in the case of missing information for any of the five social media sites. Since the goal is to assess the coordinated SMM strategy of the e-commerce retailers, popular data imputation techniques, such as using averages to replace missing values, were not employed. At the end of this process, there were a total of 417 qualified data points.

The next step was to identify prominent outliers that could adversely affect the regression analysis. The Cook's distance (D_i) and boxplot revealed the outliers. A total of 17 data outliers discovered in the boxplot were identified and subsequently deleted, which brought the final sample size to 400. Table 2 shows the descriptive statistics for the research variables.

Table 2 Descriptive statistics of research variables

	Minimum	*Maximum*	*Mean*	*Std. deviation*
Customer attraction	35,087.00	2,468,780,128.00	1,8504,294.07	133,807,512.84
Web sales	7,228,651.33	14,991,666,666.67	114,428,176.05	784,303,289.01
Facebook	763.00	35,891,924.00	2,609,200.70	5,625,763.41
Instagram	56.00	84,436,730.00	1,448,613.63	6,129,668.78
Pinterest	42.00	37,190,705.00	205,317.25	1,902,219.65
Twitter	182.00	11,218,224.00	321,157.34	1,101,537.96
YouTube	1,435.00	2,151,691,900.00	32,304,779.00	120,749,264.57
Average ticket	6	10,050	308.65	712.56

Note: N = 400, customer attraction – number of consumers visiting the site, web sales – dollar value, Facebook – number of likes, Instagram, Pinterest, Twitter – number of followers and YouTube – number of views.

Overall, the data show a good spread of values. Since the data were ranked based on annual web sales, as expected, there was some skewness, which can pose problems in regression analysis. Applying a power transformation is recommended for eliminating skewness (Cohen et al., 2003). Accordingly, the Box-Cox transformation and the related procedure for choosing lambda (L) was employed (Box and Cox, 1964). Since the choice of L for the transformation is not always clear, the shape of the distribution was used to suggest a range. The data were analysed using the IBM SPSS 26 package. A benefit of using the SPSS statistical package is that it has a built-in procedure as a part of the data preparation module for performing data transformation with multiple L values to generate the likelihood plot. Based on this information, the data were transformed using the optimum value of L(0). Post analysis did not show any further signs of skewness. The control variable, average ticket, varied across retailers depending on the product sold. For instance, the average ticket value for Amazon was 75 dollars, whereas, for BestBuy, it was 250 dollars. The mean for average ticket in the sample was 308.65 dollars. Table 3 shows the correlation scores, which indicate the degree of association among the research variables.

Table 3 Variable correlations

	Web sales	*Customer attraction*	*Facebook*	*Instagram*	*Pinterest*	*Twitter*
Web sales	1					
Customer attraction	.676	1				
Facebook	.511	.672	1			
Instagram	.367	.505	.597	1		
Pinterest	.365	.434	.584	.646	1	
Twitter	.514	.623	.670	.749	.554	1
YouTube	.295	.466	.467	.421	.239	.489

Note: N = 400, all the correlation was significant at 0.01 (two-tailed).

The results in Table 3 reveal that the predictor variables were significantly and positively associated with the dependent variables, customer attraction and web sales. Thus, social media is beneficial for e-commerce retailers in more than one way. More interestingly, there was a significant correlation between the dependent variables (.676), indicating a possible causal relationship between customer attraction and web sales. Furthermore, the correlation between the predictor variables and customer attraction was higher than those compared to web sales, which suggests the possibility of mediation. At this point, the findings provided support for moving forward with the regression analysis.

The objective of the first regression analysis was to test the causal effect of the predictor variables related to Facebook, Instagram, Pinterest, Twitter, and YouTube on customer attraction. A stepwise regression analysis using the SPSS package was performed. The benefit of stepwise regression is that the predictors in the equation do not lose their usefulness upon the introduction of an additional predictor. The subsets of significant variables are different in each step, and only a predictor displaying the best fit was included in the final model. Other parameters, such as substantial R^2 changes and the variance inflation factor (VIF), were considered when evaluating the final model. Tables 4, 4a and 4b show the results of the stepwise regression.

The findings from stepwise regression revealed three models. The best fitting model included three out of the five predictor variables, Facebook, YouTube, and Twitter, with significant R^2 change. The total explained variance was 49%. Pinterest (p-value .166) and Instagram (p-value 0.683) were not significant, and the R^2 explained remained constant at 50%. The control variable, average ticket, was not significant (p-value 0.05). Since all the predictors reflected the same phenomenon, the VIF was used to determine any influence of multicollinearity. A general rule of thumb is to check if the VIF is higher than 5, which indicates multicollinearity issues (Farrar and Gluaber, 1967). All VIF values were less than the threshold value, indicating no collinearity issues. More imperatively, this implies that each social media site has a unique contribution, and each does, in fact, individually affect customer attraction. Moreover, an optimal combination of Facebook, YouTube, and Twitter appears to most effectively enhance the customer attraction outcome variable.

Table 4 Model summary (customer attraction)

Model	R^2	*Adjusted* R^2	R^2	*F change*	*df*	*Sig. F change*
1	.452	.450	.452	327.644	398	.000
2	.481	.479	.030	22.762	397	.000
3	.492	.488	.010	8.066	396	.005

Table 4a ANOVA summary

Model		*Sum of squares*	*df*	*Mean square*	*F*	*Sig.*
1	Regression	459.898	1	459.898	327.644	.000
	Residual	558.654	398	1.404		
	Total	1,018.552	399			
2	Regression	490.191	2	245.096	184.160	.000
	Residual	528.360	397	1.331		
	Total	1,018.552	399			
3	Regression	500.739	3	166.913	127.648	.000
	Residual	517.813	396	1.308		

Table 4b Standardised regression coefficients

Model		*Std. coefficient (beta)*	*Std. error*	*P-value*	*VIF*
1	Facebook	.672	.033	.000	1.000
2	Facebook	.581	.037	.000	1.278
	YouTube	.195	.029	.000	1.278
3	Facebook	.450	.055	.000	2.929
	YouTube	.170	.030	.000	1.341
	Twitter	.219	.052	.001	3.014

Notes: Model 1: customer attraction = b_1 (Facebook).
Model 2: customer attraction = b_1 (Facebook) + b_2 (YouTube).
Model 3: customer attraction = b_1 (Facebook) + b_2 (YouTube) + b_3 (Twitter).

The next model was to analyse the effect of SMM on web sales, which was examined using stepwise regression with all five predictor variables. Once again, average ticket was included as the control variable. The regression results are shown in Tables 5, 5a and 5b.

Table 5 Model summary (web sales)

Model	*Adjusted* R^2	R^2 *change*	*F change*	*df*	*Sig. F change*
1	.262	.264	142.666	398	.000
2	.287	.026	14.800	397	.000

Table 5a ANOVA summary

Model		Sum of squares	df	Mean square	F	Sig.
1	Regression	161.239	1	161.239	142.666	.000
	Residual	449.815	398	1.130		
	Total	611.054	399			
2	Regression	177.405	2	88.703	81.206	.000
	Residual	433.648	397	1.092		
	Total	611.054	399			

Table 5b Standardised regression coefficients

Model		Std. coefficient (beta)	Std. error	P-value	VIF
1	Twitter	.514	.028	.000	1.00
2	Twitter	.291	.046	.000	2.87
	Facebook	.276	.050	.000	2.87

Notes: Model 1: web sales = b_1 (Twitter).
Model 2: web sales = b_1 (Twitter) + b_2 (Facebook).

The findings revealed that only two predictors, Twitter and Facebook, affect web sales. The R^2 change for the optimal model was significant. Interestingly, Twitter's impact on web sales was also substantial, with a total variance of 26%. The p-values for Instagram (.273), Pinterest (.113), and YouTube (.251) were not significant. The VIF was within the threshold limits. Finally, the control variable, average ticket, was not significant (p-value .235).

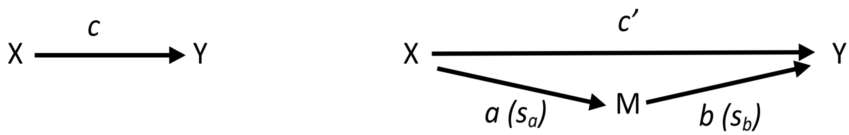
Overall, Facebook and Twitter effectively impact both the customer attraction and web sales variables. In other words, as the number of likes on Facebook increase, more consumers are attracted to the e-commerce website, which in turn improves web sales. Similarly, as the number of followers on Twitter increases, more consumers are attracted to the e-commerce website as well, which also enhances web sales. As for YouTube, as the number of views increases, more consumers are attracted to the e-commerce website. However, we cannot conclusively state that those views are associated with an increase in actual web sales.

5 Test for mediation effects

As noted in Table 3, there was a significant correlation (.676) between the two dependent variables, customer attraction and web sales. Also, the relationship between the predictor variables and customer attraction was more robust than compared to their correlations with web sales. Thus, from a statistical standpoint, it is essential to determine if customer attraction influences the relationship between the predictor variables and web sales. One possible way to do this is by analysing the mediation effects. A mediating variable can help explain the nuances of the relationship between the predictor variables and the dependent variable. In this particular study, it can provide insights as to how or why a social media site does or does not affect sales performance.

Analysing mediation effects is imperative in the present study as the optimal regression model did not include all five social media sites. Testing was done for five separate models, one for each social media site as the independent variable, with customer attraction as the mediating variable and web sales as the dependent variable. The test for mediation was performed using the procedure outlined in Baron and Kenny (1986). A four-step approach with multiple regression models was examined. Figure 1 illustrates the different modelled relationships. As shown in Figure 1, X represents the predictor variables (Facebook, Instagram, Pinterest, Twitter and YouTube), while M is the mediating variable (customer attraction), and Y is the dependent variable (web sales).

Figure 1 Mediation effect model



Step 1 involved a simple regression with X predicting Y testing for path *c* to establish if there is an effect that can be mediated. Step 2 involved testing for path *a* with X predicting M to determine if the predictor is associated with a mediating variable. Step 3 involved conducting a regression for path *b* with M predicting Y to show that the mediator affects the dependent variable. The purpose of these three steps was to establish that zero-order relationships among the variables exist. If one or more of these relationships were to be non-significant, then it would not be recommended to test for mediation effects. Table 6 provides a summary of the results of the three-step process.

Table 6 Results for pre-conditions for mediation

	Predictor	*Dependent variable*	*B*	*Beta*	*Std. error*	*P-value*
Step 1	Facebook	Web sales	.355	.511	.030	*.000*
	Instagram		.188	.367	.024	*.000*
	Pinterest		.207	.365	.026	*.000*
	Twitter		.330	.028	.514	*.000*
	YouTube		.165	.027	.295	*.000*
Step 2	Facebook	Customer attraction	.604	.672	.033	*.000*
	Instagram		.334	.505	.029	*.000*
	Pinterest		.318	.434	.033	*.000*
	Twitter		.517	.623	.033	*.000*
	YouTube		.336	.466	.032	*.000*
Step 3	Customer attraction	Web sales	.523	.676	.029	*.000*

As shown in Table 6, all of the pre-conditions were satisfied. All of the relationships were significant, which provides support to contend that some form of mediation exists. The next step then was to determine the nature of mediation through regression analysis with X (social media site) and M (customer attraction) predicting Y (web sales). If path *b* is significant, and path *c′* is insignificant, then the findings support full mediation. If both path *c′* and path *b* are significant, then the results support partial mediation. An alpha of .01 was maintained throughout the study to ensure consistency. It is important to note that the purpose of this step was not to test for a mediation effect, but to determine the form of mediation. Table 6a shows a summary of the results.

Table 6a Results for form of mediation

Model		*B*	*Beta*	*Std. error*	*P-value*	*Mediation type*
1	Facebook	.072	.103	.035	.040	Full
	Customer attraction	.469	.606	.038	.000	
2	Instagram	.018	.034	.022	.425	Full
	Customer attraction	.510	.658	.033	.000	
3	Pinterest	.050	.088	.023	.031	Full
	Customer attraction	.494	.637	.032	.000	
4	Twitter	.097	.152	.030	.001	Partial
	Customer attraction	.450	.581	.036	.000	
5	YouTube	.014	.020	.026	.535	Full
	Customer attraction	.533	.688	.032	.000	

Note: Dependent variable: web sales.

Table 6b Tests for mediation effect

Test	*Equation*
Sobel	$\text{z-value} = a * b / \text{SQRT}(b^2 * s_a^2 + a^2 s_b^2)$
Aroian	$\text{z-value} = a * b / \text{SQRT}(b^2 * s_a^2 + a^2 s_b^2 + s_a^2 * s_b^2)$
Goodman	$\text{z-value} = a * b / \text{SQRT}(b^2 * s_a^2 + a^2 s_b^2 - s_a^2 * s_b^2)$

Table 6c Aroian test results for mediation effect

Predictor	*Test statistic*	*Std. error*	*P-value*
Facebook	10.222	.028	.000
Instagram	9.223	.018	.000
Pinterest	8.162	.019	.000
Twitter	9.759	.024	.000
YouTube	8.882	.020	.000

Note: Dependent variable: web sales and mediating variable – customer attraction.

Table 6d Summary of effects

Predictor	*Total effect (c) = c′ + ab*	*Direct effect (c′)*	*Indirect effect (a * b)*	*Proportion mediated (%) (ab / c)*	*Magnitude*
Facebook	.355	.072	.283	80	Complete
Instagram	.188	.018	.170	90	Complete
Pinterest	.210	.050	.160	77	Partial
Twitter	.330	.097	.233	71	Partial
YouTube	.194	.014	.180	92	Complete

Note: Dependent variable: web sales and mediating variable – customer attraction.

The final step was to determine the significance of the mediation effect. The Aroian version of the Sobel test suggested by Baron and Kenny (1986) was employed. This is because the Aroian test does not undermine the impact of standard error and tends to be more robust than either the original Sobel test or the Goodman test (Preacher and Kelley 2011). Table 6b shows the equations for all three tests. For a detailed explanation, please refer to Baron and Kenny (1986), Sobel (1982) and Goodman (1960).

The Aroian version of the Sobel test was performed using unstandardised coefficients with the input values from the regression analysis listed in Step 2 from Table 6 and Table 6a. The testing procedure uses macros provided by Preacher and Hayes (2004, 2008). Table 6c shows the results of the tests.

The findings from the Aroian test indicated that all of the mediation effects were significant, and it is viable to conclude that customer attraction mediates the effect of SMM on web sales. The next step was to determine the magnitude of mediation – the total effect, direct effect, indirect effect, effect size, and proportion of the effect. In the case of large sample sizes ($N > 100$), it is appropriate to report the proportion of the total effect that is mediated rather than the effect size or power (Kenny and Judd, 2014). The rule of thumb is that the proportion mediated must be at least 80% to claim complete mediation. The procedure defined in Kenny et al. (1998) was employed to compute the values.

The findings listed in Table 6d reveal that customer attraction mediates the relationship between SMM and web sales. For Facebook, the association is mediated by 80%, Instagram is 90%, Pinterest is 77%, Twitter is 71% and YouTube is 92%. Table 6c shows all the significant mediation effects. The findings reveal that customer attraction mediates the impact of social media on sales performance. To be precise, as customer attraction increases, so does sales performance.

6 Discussion and implications

The primary objective of this study was to determine the effectiveness of SMM on the performance of online retailers and to help identify the optimal SMM mix. In other words, is it worthwhile for e-commerce retailers to render significant effort to formulate coordinated strategies designed to leverage the potential of social media? More importantly, as notably questioned by Hoffman and Fodor (2010), can we measure the financial impact of SMM? The findings from this study show that the coordinated use of social media does have a positive impact in the form of customer attraction and web sales performance. One interesting point is that measuring the performance of SMM does not require the use of complicated or indirect proxies. Given the increasing availability of detailed marketing and financial data, it can be as simple as calculating the returns in terms of customer response and direct sales performance.

Another critical aspect of the findings is to demonstrate that SMM research can move beyond the use of proxy variables. In particular, the results of this study reveal two available performance metrics, customer attraction and web sales performance that can have firm-level implications. Moreover, these two direct measures can address both short-term goals (attraction to the marketer's website) as well as long-term implications (increasing sales through SMM). Our findings indicate that SMM can have a significant impact on both of these variables. Moreover, as the findings show, these dimensions are interrelated, and companies should consider both of these performance dimensions in an integrated fashion, rather than treating these variables as isolated and independent factors.

For online retailers, moving on from the issue of performance metrics, the question turns to which social media sites to include in the SMM mix. The results indicate that it is not necessary to consider all five of the most prominent social media platforms. Instead, firms have the opportunity to take a somewhat selective approach. The intention here is by no means to offer a comparative analysis, but to suggest an optimal combination. Furthermore, in contrast to some studies that question the use of traditional metrics for Facebook (John et al., 2017; Leslie et al., 2017; Patel, 2015) or Twitter (Muñoz-Expósito et al., 2017), our results indicate that Facebook likes and the number of Twitter followers both had a robust influence on customer attraction and web sales performance, while YouTube views only influence customer attraction.

Given that the sample included the 500 most successful e-commerce firms as ranked by annual sales, a group of companies that should be benchmarked by smaller firms, this finding alludes to a clear hierarchy among social media sites. From a managerial standpoint, the analysis suggests that companies should ensure their presence on Facebook, Twitter, and YouTube, while leaving open the opportunity to engage with other social media platforms based on the characteristics and preferences of their unique target markets. Considering that coordinated and comprehensive SMM efforts are costly (Zhao and Zhu, 2010), taking such a selective approach can help firms more efficiently allocate their SMM budgets.

Our findings also reinforce the popular appeal of these sites. From an academic standpoint, previous studies have predominantly focused on Facebook, Twitter and YouTube (Helena et al., 2016). However, the focus has frequently been on one individual site, rather than considering them holistically. Our findings show that by combining social media platforms in the analysis, the R-square change (Tables 4 and 5) was significant. In other words, studying the combined impact of more than one social media site can help reveal more definitive implications, and shed insight on the dynamics of coordinated SMM as a whole.

7 Limitations and future research

It is also essential to identify potential limitations and future research directions. Because this study looked at the sales data of only the top 500 e-commerce retailers in the USA, it may be interesting to see if the findings are consistent in other e-commerce marketplaces across the globe, including Europe, China and India. Also, this study found that customer attraction mediated the relationship between SMM and web sales. However, there may be additional factors that can also influence the link between these variables. One possible variable to consider is the conversion rate (i.e., the proportion of orders placed to website visitors). Prior literature has often included the conversion rate as the dependent variable (Gudigantala et al., 2016). Given both the popularity and importance of this variable, it may be worthwhile to perform a multilevel mediation model at the firm level to determine if multiple mediations exist.

Another possible limitation of our study may be related to the social media metrics employed. For Facebook, in particular, there is some evidence to suggest that likes may be an overly simplistic metric. For example, contrary to what our findings may suggest, an analysis by Patel (2015) indicates that Facebook likes are not strongly correlated with more business or more engagement. Similarly, Leslie et al. (2017) conclude that liking a brand on Facebook has little effect on the purchasing habits of friends. Given the possible limitations associated with the most readily available social media metrics, future studies may wish to consider other emerging social media metrics such as brand sentiment (Moussa, 2019) or the length of a single page view session (Kamerer, 2020).

In addition, the research model was analysed with a regression technique, which was appropriate given the exploratory nature of this study. Nevertheless, future researchers may choose to incorporate structural equations modelling to more conclusively verify the causal links among the variables. Furthermore, rather than examining only the largest e-commerce retailers, regardless of the product category or target market focus, the study could be replicated or expanded upon in more specific and targeted industries. One promising approach is to study the fashion industry, as a recent Forrester Research report predicts the global online fashion market will reach $765 billion by the year 2022 (Meena et al., 2018). Thus, extending the analysis to this context may provide valuable and managerially significant insights for a growing e-commerce sector.

Finally, future researchers may seek to understand more fully the explanatory mechanisms behind our findings. Expanding the level of understanding in a field often depends on a study of the psychological aspects of consumer behaviour. For example, what are the motivating factors that led to our results? Also, future researchers may wish to examine the strategies and tactics that practitioners can deploy to better increase attraction. Similarly, how can marketers better increase engagement? These are the kinds of practitioner-focused issues that often define the overall contribution of a particular research stream.

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