The Role of Social Media Content Format and Platform in Users' Engagement Behavior

Article *in* Journal of Interactive Marketing · September 2020

DOI: 10.1016/j.intmar.2020.05.001

3 authors:

Hamid Sha
University of Auckland

Rebecca Dolan
University of Adelaide

Mona Rashidirad
University of Sussex

Available online at www.sciencedirect.com

ScienceDirect

Journal of Interactive Marketing 53 (2021) 47–65

JOURNAL OF INTERACTIVE MARKETING

www.elsevier.com/locate/intmar

The Role of Social Media Content Format and Platform in Users' Engagement Behavior

Hamidreza Shahbaznezhad& Rebecca Dolan& Mona Rashidirad *

[a] University of Auckland, Auckland, New Zealand
[b] University of Adelaide, Adelaide, South Australia, Australia
[c] Sussex Business School, University of Sussex, Brighton, UK

Abstract

The purpose of this study is to understand the role of social media content on users' engagement behavior. More specifically, we investigate: (i) the direct effects of format and platform on users' passive and active engagement behavior, and (ii) we assess the moderating effect of content context on the link between each content type (rational, emotional, and transactional content) and users' engagement. The dataset contained 1,038 social media posts and 1,336,741 and 95,996 fan likes and comments, respectively based on Facebook and Instagram. The results reveal that the effectiveness of social media content on users' engagement is moderated by content context. The findings contribute to understanding engagement and users' experience with social media. This study is a pioneering one to empirically assess the construct of social media engagement behavior through the effects of content types and content contexts on a dual social media platform.

Keywords: Content type; Engagement behavior; Content context; Media richness theory; Facebook; Instagram

Introduction

Due to the ongoing popularity of social media across the world, firms' social networks are growing at an increasingly rapid pace, intending to build online engagement among their customers (Hallock, Roggeveen, & Crittenden, 2019). Facebook, the most popular social media platform, has recorded a monthly active user rate of 2,375 million in April 2019 (Statista, 2019). Likewise, the number of monthly active Instagram users has increased from 90 million in January 2013 to 1,000 million in June 2018 (Statista, 2019). Correspondingly, social media content directed at customers continues to proliferate as customers' digital spending increases (Malthouse, Calder, & Vandenbosch, 2016). Social media advertising revenue has grown 30.6% in the U.S. in 2018 alone to $28.9b (PwC, 2019). Firms are cognizant of this and are ever-increasingly investing in content creation and distribution within the social space. However, such marketing investments will not succeed unless marketers understand how to effectively create and distribute their content within these platforms to promote their desired outcomes, with one of the most frequently listed desired outcomes being customer engagement (Lee, Hosanagar, & Nair, 2018).

Previous studies (e.g., Gavilanes, Flatten, & Brettel, 2018) have drawn attention to the relationship between social media advertising efforts and the resultant customer engagement. However, the pertinent literature is limited in several ways. For example, much of the earlier research was largely conceptual (e.g., Ashley & Tuten, 2015; Dolan, Conduit, Frethey-Bentham, Fahy, & Goodman, 2019; Dolan, Seo, & Kemper, 2019), or offered a limited conceptualization of social media engagement behavior, mainly through numbers of likes, shares or comments (e.g., Cvijikj & Michahelles, 2013; De Vries, Gensler, & Leeflang, 2012). Our understanding of social media content design was also limited, with earlier scholars using

* Corresponding author.
E-mail addresses: H.Shahbaznezhad@Auckland.ac.nz (H. Shahbaznezhad), Rebecca.Dolan@Adelaide.edu.au (R. Dolan), M.Rashidirad@Sussex.ac.uk (M. Rashidirad).

https://doi.org/10.1016/j.intmar.2020.05.001
1094-9968

broadly defined and limited content types, such as informational vs. entertaining (De Vries et al., 2012) and employing a singular social media platform to test social media engagement, e.g., Facebook or Instagram (e.g., Gavilanes et al., 2018; Kim, Spiller, & Hettche, 2015; Lee et al., 2018). Also, despite the numerous insights from previous work on the role of content type on users' engagement, very few studies have considered the role of content format, e.g., picture, video, etc. and the relationship with the choice of social media platform (e.g., Facebook vs. Instagram) on predicting users' engagement behavior. Finally, most of the relevant studies employ survey methods to collect primary data (see Voorveld, Van Noort, Muntinga, & Bronner, 2018), yet this is not comparable with actual secondary data.

In response to the aforementioned limitations, this study aims to provide a more in-depth and holistic investigation of this phenomenon by considering: (i) a more thorough range of social media content strategies, specifically 12 content types integrated into three overarching strategies, (ii) the role of the platform type by collecting data from both Facebook and Instagram, and (iii) the role of the content format in terms of richness, i.e., comparing both photo and textual social media posts. To achieve this, we utilize the Facebook and Instagram APIs to capture data of two Pacific Airlines and empirically demonstrate how these different contexts and types of social media content act as drivers of user engagement. By qualitative content-coding of the firms' posts, quantitative sentiment analysis of user comments and regression analysis we connect firms' content management activities to user engagement behavior.

This research provides managers with guidance for developing social media strategies, investigating the distinct effects of social media content (rational, emotional, and transactional) along with content context (platform type and content format), and lag effects between posts on active and passive engagement. In our study, we carefully explore how and why different platform environment will lead to active or passive engagement. Finally, in this study, we consider the important nature of engagement influence by considering possible lag effects between posts, such that the interactivity and engagement generated by one post may have carry-over effects on the engagement level of subsequent posts. In so doing, we go beyond numbers of likes and comments on posts to measure engagement.

The remainder of the paper is structured as follows. First, we introduce the background of the study, namely, the role of social media and users' engagement. Second, we introduce the conceptual model and hypotheses of the study. The research context in which the study is conducted is then presented, followed by an overview of the study design. After presenting the results of the study, we outline the key findings, implications, and important contributions and limitations of the study, leading to a range of ideas recommended for further research.

Literature Review

Users' Engagement

The emergence of social media platforms has dramatically altered the role of customers from passive observers of content, to active participants, who are now the co-producers (Lee et al., 2018) and co-creators of content through their online interactions and behaviors (Dolan, Conduit, et al., 2019). Behavior that reflects engagement with social media includes customers' creation of, contribution to, or consumption of brand-related content within a social network (Hallock et al., 2019; Muntinga, Moorman, & Smit, 2011). The extent of engagement differs from simple types of engagement (e.g., "liking" a post on Instagram) to higher types of customer engagement in co-creation activities (e.g., posting reviews) (Malthouse, Haenlein, Skiera, Wege, & Zhang, 2013; Muntinga et al., 2011).

The growing prevalence of social media has seen a focus emerge from both academics and practitioners on the concept of engagement in social media platforms (Brodie, Ilic, Juric, & Hollebeek, 2013). Customers' engagement has been studied in many fields, including psychology (e.g., Hallberg & Schaufeli, 2006), education (e.g., Baron & Corbin, 2012), management (e.g., Saks, 2006), marketing (e.g., Hollebeek, 2011; Van Doorn et al., 2010), and information systems (e.g., O'Brien & Toms, 2008). Within the context of digital marketing, scholars (e.g., Brodie et al., 2013; Wirtz et al., 2013) conceptualized the concept of engagement and attempted to empirically validate its measurement scales (see Hollebeek, Glynn, & Brodie, 2014). Van Doorn et al. (2010) define it as "a customer's behavioural manifestations that have a brand or firm focus, beyond purchase." There are various focal objects of customer engagement including product or service offerings (e.g., Brodie, Hollebeek, Jurić, & Ilić, 2011), activities and events (e.g., Vivek, Beatty, & Morgan, 2012), and media (e.g., Calder, Malthouse, & Schaedel, 2009). Some (e.g., Malthouse et al., 2013; Muntinga et al., 2011) recognized the properties of engagement, such as intensity, and examined its various aspects and antecedents (see also De Vries et al., 2012; Gummerus, Liljander, Weman, & Pihlström, 2012; Wirtz et al., 2013). Engagement is interactive and context-dependent and is understandable through an examination of each of its various aspects, known as service experiences (see Brodie et al., 2011; Calder et al., 2009; Coulter, Gummerus, Liljander, Weman, & Pihlström, 2012). This research explores the behavioral aspects of the concept, consistent with previous studies of engagement in social media (e.g., Coulter et al., 2012; Dolan et al., 2016; Van Doorn et al., 2010). According to Dolan, Conduit, Fahy, Brodie, et al. (2016), there are six types of social media engagement behavior on fan pages: creating, contributing, destructing (known as active engagement behaviors), consuming, dormancy, and detaching (known as passive and/or more individualized forms of engagement).

The interactive characteristics of engagement behavior may lead to different levels of intensity. In a most recent study on engagement intensity levels, Dolan, Conduit, Fahy, Brodie, et al. (2016) suggest two typologies that encompass the six behavioral groups (referred above). As they argue, it can be passive (low) or active (high) and also positive or negative. Passive engagement is defined through the behavior of a member browsing an online group and making the most of the benefits accessible, while not participating in any community activities (Preece, Nonnecke, & Andrews, 2004). In contrast, active engagement is determined through the behavior of members highly interested to be engaged in an online community by participating in activities, creating messages, disseminating information, and providing emotional support to others (Casaló, Flavián, & Guinalíu, 2007). There are different metrics to measure the intensity of passiveness or activeness of social media engagement (see Peters, Chen, Kaplan, Ognibeni, & Pauwels, 2013). For instance, Alhabash et al. (2013) describe liking (as "affective response") and commenting as ("active and public deliberation"), as active social media behaviors, while reading content and clicking are examples of passive engagement behaviors (Dolan, Conduit, Fahy, Brodie, et al., 2016). This research focuses on active engagement behavior. To address how consumers feel about the content presented on the fan page, this research also considers the sentiment of the comments, which can be an indication of positively valenced engagement (Van Doorn et al., 2010) and/or negatively valenced engagement (Hollebeek & Chen, 2014).

Social Media Content Types and Users' Engagement

Drawing on prior studies, social media content which influences engagement has been conceptualized into three main categories of *rational* (also referred to as informational, functional, educational, or current event), *interactional* (e.g., experiential, personal, employee, brand community, customer relationship, cause-related), and *transactional* (also referred to as remunerative, brand resonance, sales promotion). Within these three overarching themes of social media content, scholars have attempted to investigate the impact of various content types on engagement behavior. Table 1 presents a summary of these studies.

As shown in Table 1, several studies have investigated the role of rational content on social media, but providing mixed and inconsistent results in facilitating passive or active engagement behaviors online. For example, while Coelho, Oliveira, and Almeida (2016) found no significant relationship between the effect of rational content on engagement on both Facebook and Instagram, Cvijikj and Michahelles (2013) found empirical support in the form of both likes and comments. This study was however limited to one platform (Facebook) within the singular sector of food and beverages. Conversely, more recent research by Dolan, Conduit, et al. (2019) empirically demonstrated that rational content influences engagement in the form of likes (passive engagement), but it does not influence more active engagement (such as comments). This study was, however, again restricted and limited by platform (Facebook only) as well as context (only wine brands were explored). Albeit some suggestions that rational content appeals are not as effective as emotional appeals in customer engagement, the research of others offer contradicting results based on static traditional media settings (e.g., Aaker, Stayman, & Hagerty, 1986; Liu & Stout, 1987).

Similarly to the role of rational content, several scholars have presented conflicting and inconsistent results regarding the relationship between the use of emotional social media content and its influence on engaging fans. Dolan, Seo, and Kemper (2019) explored relational and entertaining content as two forms of emotional appeals used in social media content. They found out that entertaining content influences engagement in the form of likes, but did not affect active engagement in the form of comments. In another study, Tafesse (2015) explored the role of entertaining content disseminated by automotive brands in the UK on Facebook. They suggested that humorous, funny, and artistic content (entertaining) is more likely to be liked on Facebook than a more serious content involving product and prices (informational content). The authors did not, however, consider, the relationship between entertaining content and more active engagement behavior, such as comments. Other scholars explored how the role of entertaining/emotional content in facilitating engagement might vary across business-to-business (B2B) and business-to-consumer (B2C) Facebook pages. For instance, Swani, Milne, and Brown (2013) found that in the B2C setting, emotional content generates more likes than in B2B firm Facebook pages, and it generated more engagement (likes) in services versus product pages. This demonstrated the importance of considering moderating variables (such as context) in gaining a deeper understanding of the relationship between content type and engagement. However, the findings of Swani et al. (2013) are not generalizable, as the authors underestimated the important roles of the message types (e.g. video, images, and text) and platforms of engagement (any other than Facebook).

The final section of Table 1, depicts studies that have considered the role of transactional content. Defined in different ways across each study, the idea of transactional content focuses on the use of direct calls to purchase and the promotional approach (Swani et al., 2013) within social media content. Transactional content covers sales promotion and brand resonance contents. This may include monetary incentives, giveaways, prize drawings, or monetary compensations (Füller, Bartl, Ernst, & Mühlbacher, 2006). Some users expect to gain a reward, such as a monetary incentive, job-related benefit, or personal needs (Muntinga et al., 2011). The work of Cvijikj and Michahelles (2013) and Dolan, Seo, and Kemper (2019) explored the concept of transactional content under the label of "remunerative" content. Cvijikj and Michahelles (2013) results are consistent with the work of Swani et al. (2013) showing that the use of remunerative content significantly reduced the number of likes (passive engagement). Interestingly, they found that remunerative content increases the number of comments (active engagement). However, Dolan, Conduit, et al. (2019) found conflicting results, indicating that the use of remunerative content has a significant, positive effect on likes and shares (passive engagement), but not comments (active engagement). Research has also shown that components of transactional content, such as price incentives, discounts, and deals, create an emotional appeal. For instance, according to Zielke (2011) value perceptions emerging from remunerative content can affect emotions and provoke responses, either positively (e.g. enjoyment of low prices) or negatively (e.g. shame over discount shopping) (Dolan, Seo, & Kemper, 2019).

Table 1
A summary of studies on three main types of content and its impact on engagement behavior.

Authors	Research type	Definition of content	Impact on engagement	Measure(s) of engagement	Platform
Rational content (Informational, functional, educational and current event)					
Dolan, Conduit, et al., keep comma through out. (2019)	Empirical	Informational content provides users with resourceful and helpful information.	Significant effect	Likes, shares, comments	Facebook
Coelho et al., (2016)	Empirical	Content about events, places, opportunities, people, or celebrities, directly connected to a brand or otherwise	Non-significant effect	Likes, comments	Instagram Facebook
		Posts, with photo and video media, directly connected to brands or otherwise	Significant for likes on both platforms Significant for comments on Instagram Non-significant for comments on Facebook		
Ashley and Tuten (2015)	Conceptual	Utility or functionality of the product/ service.	–	–	Twitter, Facebook, MySpace, forums, and blogs
Kim et al., (2015)	Empirical	News, information, or story about the firm or its products, an event, program or campaign sponsored by the firm, a picture(s) or video of its employee, management or staff	The task-oriented content received more likes, comments and shares than both interaction- and self-oriented content. No significant difference between interaction- and self-oriented content.	Likes, comments, shares	Facebook
Tafesse (2015)	Empirical	Product specification, product reviews, and product recommendations	Non-significant effect	Likes, shares	Facebook
Cvijikj and Michahelles (2013)	Empirical	In form of traditional advertisement, thus containing information about specific products, brand or the firm	Significant positive on Likes Significant positive on comment Non-significant negative on share	likes, comments	Facebook
De Vries et al. (2012)	Empirical	Information about the brand or product	Non-significant effect for both likes and comments	Likes, comments	NA
Interactional content (Experiential, personal, employee, brand community, customer relationship and cause-related)					
Dolan, Seo, and Kemper (2019)	Empirical	Entertaining content refers to the extent that is fun and entertaining to media users. Relational content refers to the extent that meets the consumer's need for integration and social interaction and desire for social benefits.	Significant positive effect of entertaining content on likes	Likes, shares, comments	Facebook
Coelho et al. (2016)	Empirical	A fan is responsible for the main idea of post, or for sending the photo.	Non-significant effect	Likes, comments	Instagram Facebook
		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	Significant effect for likes on Instagram Non- significant effect for the rest		
Ashley and Tuten (2015)	Conceptual	Psychological/social needs- how it will make them feel. Also an echoing between the image and words (e.g., buried treasure).	–	–	Twitter, Facebook, MySpace, forums, and blogs
Swani et al. (2013)	Empirical	Advertising the name of the firm Motivating individuals to express their feeling by engaging with the message	Significant negative effect Significant positive effect	Likes	Facebook
De Vries et al. (2012)	Empirical	Fun, exciting, cool, and flashy – do have a positive effect on attitude toward the ad (Taylor, Lewin, and Strutton 2011), attitude toward the brand, and the desire to return to the website (Raney et al. 2003).	Non- significant effect	Likes, comments	NA
	Conceptual		–	–	

Table 1 (*continued*)

Authors	Research type	Definition of content	Impact on engagement	Measure(s) of engagement	Platform
Ashley and Tuten (2015)		How they will experience sight, sound, taste,touch,smells.			Twitter, Facebook, MySpace, forums, and blogs
Cvijikj and Michahelles (2013)	Empirical	Entertaining posts written in a form of teaser, slogan, or word play, most of those explicitly asking for an engagement from fans.	Significant positive on like Significant positive on Comment Significant positive on Share	Likes, comments	Facebook
Kim et al. (2015)	Empirical	A personal statement, proverb, or maxim celebrating a special day, event or person, opinion on a certain social issue or topic, weather or season Talks about entertainment Asking to "Like", "Comment" or "Share" the post Asking to answer a question, to vote, to fill in the blank, or to visit a link A picture(s) or video of its consumers, fans, brand users. or event participants	The task-oriented content received more likes, comments and shares than both interaction- and self-oriented content. However, there was no significant difference between interaction- and self-oriented content.	Likes, comments, shares	Facebook
Tafesse (2015)	Empirical	Brand posts about humorous items, artistic works, competitions, and events	Significant effect on likes Non-significant on share	Likes, shares	Facebook
Transactional content (Remunerative, brand resonance and sales promotion)					
Dolan, Conduit, et al. (2019)	Empirical	Remunerative content provides monetaryorincentiverewards.	Significant positive effect on likes and shares	Likes, share and comments	Facebook
Coelho et al. (2016)	Empirical	Posts with quizzes, which promote participation of followers through rewards	Likes supported for both platforms Comments unsupported for both platforms	Likes comments	Instagram Facebook
Ashley and Tuten (2015)	Conceptual	How product/service is different from others Do they compare their products to a competitor(s)? If so, is it direct comparison	–	–	Twitter, Facebook, MySpace, forums, and blogs
Kim et al. (2015)	Empirical	Generating revenues. Advertising a certain brand or product with persuasive messages or visuals. A new product or service announcement. Online coupons, discounts, contests, or sweepstakes.	The task-oriented content received more likes, comments and shares than both interaction- and self-oriented content. No significant difference between interaction- and self-oriented content.	Likes, comments, shares	Facebook
Tafesse (2015)	Empirical	Product specification, product reviews, and product recommendations	–	Likes, shares	Facebook
Swani et al. (2013)	Empirical	Content encouraging an immediate sale	Non-significant negative effect	Likes	Facebook
Cvijikj and Michahelles (2013)	Empirical	In a form of sweepstakes organized	Significant negative on like. Significant positive on comment. Non-significant negative on share	Likes, comments, shares and interaction duration	Facebook

These varied results indicate a need for further and more robust theoretical and empirical examination of the role of different content types in social media to fully understand their use and relationship with engagement behavior. Moreover, as listed in Table 1, previous studies have often focused on a singular platform or singular format context, limiting our understanding of the diverse nature in which content can be presented and delivered to social media users. In this study, all three main types of content, including rational, emotional, and transactional content is systematically explored on a dual platform of Facebook and Instagram to assess whether and how it may promote users' engagement behavior.

Conceptual Model and Hypotheses

Theoretical Background: Media Richness Theory

Media Richness Theory is a widely known theory of media use which has been applied to multiple fields (e.g., Kaplan & Haenlein, 2010; Liu, Liao, & Pratt, 2009; Tseng, Cheng, Li, &

Teng, 2017). This theory regards the objective characteristics of media channels which determine their ability to carry information (Tseng et al., 2017). Media richness comprises four dimensions: (i) the ability to use multiple information channels to handle information cues simultaneously, (ii) the ability to facilitate rapid feedback, (iii) the ability to establish a personal focus according to the need and situation of the media user, and (iv) the ability to utilize symbols or alternatives in a language to convey information (Trevino, Lengel, & Daft, 1987). The underlying message of this theory is that communication efficiency can be improved by matching media to users' information needs (Daft & Lengel, 1986).

Whilst a majority of studies compare richness between forms of media, e.g. telephone vs. direct mail marketing, the new communication landscape provides marketers with an opportunity to provide both “rich” and “lean” advertising and marketing content within a single media type such as a website. Media richness has been applied in the field of online and digital marketing (Shaw, Chen, Harris, & Huang, 2009). Online rich media includes a range of interactive methods that display motion and exploit sensory traits such as video, audio, and animation (Rosenkrans, 2009). The term ‘‘rich media’’ in this context provides an umbrella expression to describe online content that has multimedia elements such as sounds, video, or content that moves when a user clicks on the page that features the content (Shaw et al., 2009). Previous research has found that face-to-face meetings have more richness than communication media and written documents, as the latter lacks verbal feedback cues (such as facial expression, the direction of gaze, posture, and dress) (King & Xia, 1997). However, in a virtual, socially online environment, individuals can communicate in a style that is similar to face-to-face communication, which results in an increased richness of content (Cheung et al., 2011) and improved customers' experience (Li, Dong, & Chen, 2012). Social media posts differ in the degree of richness they possess, measured by the amount of information they transmit in a given time interval (Cvijikj & Michahelles, 2013; De Vries et al., 2012). While online rich media (e.g., video, audio, and animation) which includes a range of interactive and motional methods exploits several sensory-related characteristics, content lower in richness (e.g., photos or images) stimulates few or basic senses (Rosenkrans, 2009).

Research Hypotheses

Given the significance of media richness, it is somewhat surprising to find that little empirical research has focused on exploring its role in influencing how customers' engagement with that given media. Kim et al. (2015) found posts with photo content stimulated higher customers' engagement (in forms of likes, comments, and shares), compared to “richer” content such as video posts. In another study, Sabate, Berbegal-Mirabent, Cañabate, and Lebherz (2014) proposed that while both photo and video contents increase engagement in form of likes (i.e., passive), surprisingly, the posts which contain video content did not significantly affect active engagement (comments). While much of the research has explored the research phenomenon on a singular platform of Facebook, the findings are not robust and consistent enough to discourage us to further explore the issue in more details on different platforms. Thus, drawing on Media Richness Theory (Daft & Lengel, 1986), and consistent with some prior research (e.g., Cvijikj & Michahelles, 2013; De Vries et al., 2012; Moro, Rita, & Vala, 2016), we argue that social media posts with richer content (e.g., videos) are more effective in social media communication compared to lower rich content (e.g., photos), and therefore will facilitate behaviors that reflect greater engagement in the form of active engagement behavior. We, therefore, hypothesize the following:

H1a. High media richness (video format) positively stimulates active engagement behavior.

H1b. Low media richness (photo format) positively stimulates passive engagement behavior.

Previous studies on social media content and online engagement have provided little insights into the important role of the *type* of social media platform. However, most brands commonly utilize a multi-platform social media strategy to share the same content across platforms in an attempt to reach a wider audience. To illustrate, according to Globalwebindex (2019) Internet users have an average of seven different social media accounts on different platforms. Most previous research in this field, however, has often focused on either social media in general (e.g., Muntinga et al., 2011; Okazaki, Rubio, & Campo, 2014; Van Noort, Antheunis, & Verlegh, 2014) or only one specific social media platform, such as Facebook (e.g., Nelson-Field, Riebe, & Sharp, 2012), YouTube (e.g., Liu-Thompkins, 2012; Walther, DeAndrea, Kim, & Anthony, 2010), Twitter (e.g., Liu, Burns, & Hou, 2017; Sook Kwon, Kim, Sung, & Yun Yoo, 2014;), or Pinterest (Phillips, Miller, & McQuarrie, 2014). More recently, Voorveld et al. (2018) introduced the importance of a multi-platform perspective, examining the differentiating role of social media platform type on customers' engagement with social media and social media advertising. Engagement is demonstrated to be highly context-specific, comprising of various types of experiences on each social media platform such that each is experienced uniquely (Voorveld et al., 2018).

We expect differences in engagement behavior to emerge across platforms, as the user experience and devices may be different. To begin with, while Facebook users mostly (96%) access Facebook through a mobile device via the Facebook App, 25% of Facebook users also access the site through desktops and/or laptops (Khoros, 2020), unlike Instagram which offers largely app-only access (Khoros, 2020). A social media site with website presence (and therefore desktop/laptop use), such as Facebook, may be conducive to more active engagement as users on desktop are generally at home or in their office purposefully browsing the internet. Comparatively, mobile users may be commuting, waiting for an appointment, or out and about and easily interrupted (Enge, 2019). We can, therefore, assume that desktop users may be more likely to actively engage (typing a comment), compared to mobile users. Given Facebook has a strong website presence and Instagram does not, we expect that active engagement is higher on

Facebook compared to Instagram. Accordingly, the second research hypothesis of this study aims to assess the distinctive role of the platform type in relation to social media engagement behavior. We therefore propose the following:

H2. Social media engagement behavior (in the form of active or passive engagement) varies depending on the social media platform (Facebook vs. Instagram).

The last three research hypotheses in this study investigated the moderating role of social media context (both format and platform, as discussed above) on the relationship between the type of social media content (rational, emotional, and transactional) and social media engagement behavior. As discussed earlier, previous studies of social media content have often focused on identifying the role of content types in a singular platform or singular format context, limiting our understanding of the diverse nature in which content can be presented and delivered to social media users.

First, we posit that the extent to which social media content facilitates social media engagement behavior is moderated by the format of the content (see H3a, H4a, H5a). We expect differences in this relationship to unfold across the three types of content studied (rational, emotional, and transactional). For example, emotional content may be best suited to a higher media richness format, as it can convey greater levels of emotional stimuli such as music and movement, compared to a photo post.

Previous studies have explored motivations for use of various social media platforms providing a relevant foundation for understanding why engagement behaviors may differ across platforms for each content type. For example, Voorveld et al. (2018) found that Facebook is associated with engagement experiences related to socially interactional and topical content. They suggest that Facebook is used to allow people to correspond with others, share something with others and to be quickly informed and get up to date. The authors found that although Facebook content made users sad or disturbed in about 15% of the moments, it also provides them with enjoyment, satisfaction, or relaxation. Comparatively, Instagram scored higher than Facebook on the pastime and topicality dimensions, again often used to fill empty moments, and was perceived by users as a social medium that ensured they were quickly informed and up to dated (Voorveld et al., 2018).

Such findings on the differences in social media engagement experiences across platforms suggest that the type of social media content that is effective in driving engagement behavior may vary, depending on the platform. To the best of our knowledge, previous literature is yet to identify how the various types of content (e.g., rational compared to emotional and transactional) would be suited to certain platforms to promote social media engagement. The hypotheses relating to the moderating role of social media context (format and platform) on the relationship between social media content types and social media engagement behavior are outlined as follows:

H3. The relationship between the presence of rational social media content and social media engagement behavior is moderated by the (a) format and (b) platform of the content.

H4. The relationship between the presence of emotional social media content and social media engagement behavior is moderated by the (a) format and (b) platform of the content.

H5. The relationship between the presence of transactional social media and social media engagement behavior is moderated by the (a) format and (b) platform of the content.

The research conceptual framework is illustrated in Fig. 1.

Methodology

Research Context

Social media has significantly changed the tourism industry, switching customers' role from passive to active users (Quach & Thaichon, 2017) who search for information, engage in collaborative planning, and memorialize travel experiences through various engagement behaviors, e.g., posting, messaging, and media sharing (Dolan, Seo, & Kemper, 2019; Zeng & Gerritsen, 2014). Although tourism research in social media context is still in the early stages, scholars (e.g., Luo & Zhong, 2015; Shu & Scott, 2014) have commonly acknowledged the positive effects of social media on travel sector and highlighted the significant role of social media in customers' engagement (e.g., Harrigan, Evers, Miles, & Daly, 2017).

In this research, we empirically investigated data of two international firms, highly active on their social media brand fan pages on two popular social networking platforms, Facebook and Instagram. To verify our research hypotheses, we controlled for the industry and focused on a singular industry—air travel. Airlines are one of the main and inseparable parts of the tourism industry, and, as large-scale service providers, frequently engage with a large customer base. Thus they are highly sensitive to customers' views/complaints (Dolan, Seo, & Kemper, 2019). Airlines' products and services are limited and, thus, their effects on social media engagement behavior are not largely heterogeneous. Also, from customer communications and public relations' point of view, airlines have exclusive touch points all around the globe (Shahbaznezhad, 2018). Further, airline customers have high involvement experience with airline services and their comments are current and effective (Dijkmans, Kerkhof, & Beukeboom, 2015). Hence, for airlines, developing high-quality campaigns and a strong presence on social media is critical for customer engagement (Shahbaznezhad, 2018). To explore our research hypotheses within this sector, we obtained data social media engagement data from two large airline companies—namely Air New Zealand and its low-cost competitor, Jetstar. Our data collection process is outlined below.

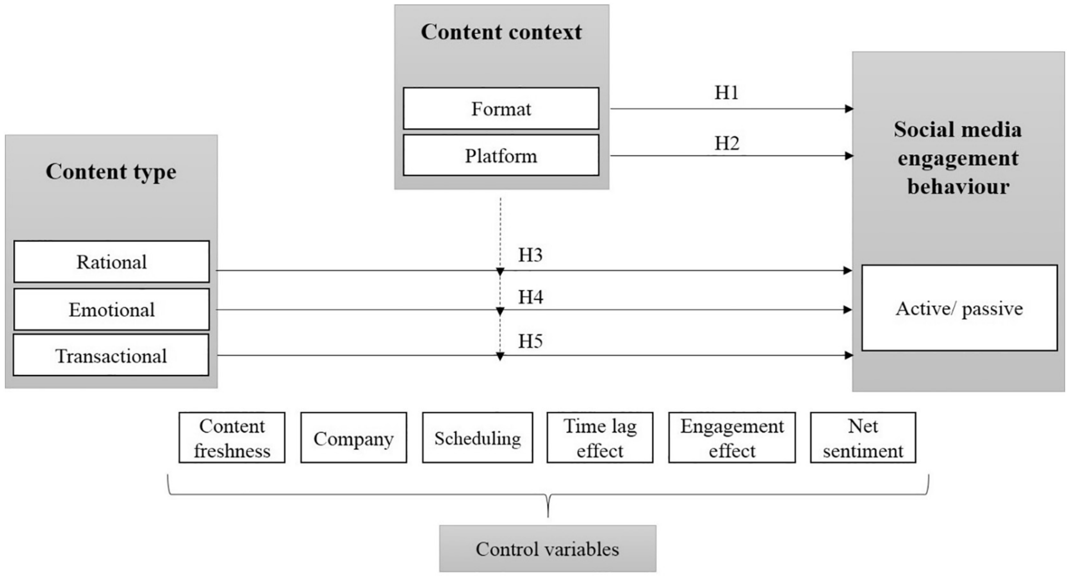

Fig. 1. Research conceptual framework.

Sampling and Data Collection

The data of this study were collected from two pacific airlines, i.e., Air New Zealand and Jetstar Australia. Data were captured across 12 months, including all posts made and their corresponding engagement metrics of likes and comments. The final dataset contained 1,038 social media posts, 1,336,741 likes, and 95,996 comments. Of 1,038 posts, 579 were collected from Air New Zealand, comprising 308 posts published on Facebook and 271 on Instagram. The remaining 459 posts were collected from Jetstar Australia, comprising both Facebook (148 posts) and Instagram (311 posts). We also explored the effect of post timing and community size on customers' engagement based on two social media platforms. This process generated four sub-sets of data (2 airlines × 2 platforms), allowing a systemic analysis of brand post strategy and liking/commenting engagement behavior across and between brands and platforms.

Operationalization of Variables

To capture the interaction between the firms and their current customers, we gathered data about firms and users' activities and interactions on firms' fan pages (Facebook and Instagram). Overall, our variables fall into two categories: (i) firm-centric and (ii) user-centric. Firm-centric variables are independent, moderating, and control variables in the conceptual model of the study (see Fig. 1) and capture firms' effort in the content generation (see Shahbaznezhad, 2018). These variables enable us to explore firms' social media content management (independent and control variables). On the other hand, the user-centric variables (dependent variables) show users' reactions to firms' content in the form of engagement on social media fan pages (Hoffman & Fodor, 2010).

Independent Variables

We relied on qualitative content analysis approach to operationalize the independent variables (the type of content). A content analysis deals with the operationalization of variables, which is an exhaustive, exclusive, and enlightening process (Krippendorff, 2013). Codes must deconstruct the focal content in a way that it would be analytically relevant and interesting (Shahbaznezhad, 2018). To ensure this, codes should be based on previously established norms in the literature (Riffe, Lacy, & Fico, 2014) in addition to being relevant to the research questions. Accordingly, the measures selected for each variable matched the conceptualizations of the unit of analysis as previously specified in the literature. We employed two trained English native speakers for coding of each social media post. They were asked to code over 100 messages during the training sessions (see also Swani et al., 2013). The intercoder reliability was calculated for all independent variables using Rust and Cooil's (1994) proportional reduction in loss index (PRL). Based on this study, a value of 0.70 is acceptable whereas 0.90 is desired. All reliability scores were high and above the desired level (0.96). Subsequently, each coder coded the whole dataset and, finally, both codes merged. After developing the full coding scheme and custom dictionaries, we coded the content in a binary manner, as applied in previous work (e.g., Tafesse, 2016). Where a type of social media content was present, it was coded as 1, while its absence was recorded as 0. In addition, each sub-category was coded as 1 or 0, which allowed for the level of content to be calculated for each content category. Each type of content contained four sub-categories, although the maximum number of content items that any post had was 4; this means that content levels were coded from 0 to 4. The total number of posts was 1,038. The number of posts coded as containing any form of informational content was 957 (92.2% of total posts), the number for emotional content was 664 (63.9% of total posts) and the number for transactional content was 652 (62.8% of total posts).

Dependent Variables

To operationalize the dependent variables, we relied on a quantitative machine learning approach. The number of comments and number of likes was calculated by counting the users' activities for every single post. Table 2 provides a summary statistic of the dependent variables.

Control Variables

We control for important variables including content freshness, company/industry, scheduling, time lag effect, and net sentiment. Content freshness addresses the effect of a firm's timing strategy for updating posts on its fan page (Ashley & Tuten, 2015). Content freshness refers to the reverse difference of one post to its previous post (Li, Po, Hsiung, Candan, & Agrawal, 2003). The lower the value, the "fresher" is the content. Secondly, we control for the industry by selecting to only investigate airlines. Our empirical research was conducted to apply the conceptual framework to a dataset derived from two major pacific airlines, i.e., Air New Zealand and Jetstar. We selected the airline industry, with limited service to control for homogeneity of product type, in addition to controlling the indirect effect of social media behavior. We included a full-service airline (Air NZ) along with a budget/low-cost airline (Jetstar) to enable comparison.

We also controlled for post scheduling. Post scheduling is considered as a key consideration for managers when designing their social media strategy (Shahbaznezhad, 2018). Recent research has indicated that the time of the day at which the post is made can be a predictor of user engagement (Kanuri, Chen, & Sridhar, 2018). Sabate et al. (2014) advised managers to schedule the delivery of their content for the afternoon if they wish to increase the number of likes and shares received on a post. Our post scheduling variable has 24 data points (24 possible hours) in our initial dataset. However, we decided to use dummy coding for post scheduling, so we split the timing into two sections: The posts made from 8 am to 5 pm (working hours) was labeled 1, and posts made from 5 pm to 8 am (evening) as 0. This was done to decrease the effect of unwanted variance due to having numerous independent variables in our framework.

The fourth control variable was the time lag effect. We assume that social media engagement behavior (likes and comments) of each post may depend on the social media engagement behavior (likes and comments) of the last post generated by a firm. This is referred to as the time lag effect. To measure the role of the time lag effect, we first addressed the potential issue of endogeneity and simultaneity. This is because some engagement behavioral patterns are unobservable to researchers, but they could be correlated with our dependent variables (i.e., number of likes and comments for each post).

Another control variable that is considered in this research is the engagement effect. Engagement effect is the effect of passive behavior (likes) on active behavior (comments) and vice versa, for the same post. We can assume that a post may stimulate more likes, once it has more comments (perhaps increasing its impressions/views, or virality). Similarly, a post probably provokes more comments, once it has more likes. Finally, the potential effect of posts' net sentiment was carefully controlled. The sentiment of a post or comment can be positively (Van Doorn et al., 2010) or negatively (Hollebeek & Chen, 2014) valenced. Positiveness/negativeness was measured as the percentage of positive/negative posts to the total number of posts (Liu, 2012). The last control variable is the net sentiment. The sentiment of the comments was then analyzed using sentiment 140 package in R. Using this algorithm, each comment was classified as positive, negative, or neutral.

Analysis

Validity Checks

To check the research validity, three different methods have been employed in this study, which are described as follows.

Train and Test Sets

We trained the dataset based on the random sample (70%) and tested it with train set. The average error percentages were 7.8% for the number of likes and 5.5% for the number of comments. The result of the regression output is presented in Table 3.

For the statistical comparison between the estimated value and real value, "Paired Samples Test" was conducted (see Table 4). The results of the test were non-significant for both dependent variables, i.e., likes and comments. This means there is no significant difference between the estimated and real values. The method used is called the Mean Absolute Percentage Error (MAPE). We then captured the percentage of the error from the original/real value of the variable. The null hypothesis (H0) assumes that the true mean difference (μd) is equal to zero.

Table 2
Summary statistic of dependent variables.

			Number of likes	Number of comments	Comments positiveness	Comments negativeness
Air New Zealand	Facebook	Sum	590,487	65,394	–	–
		Average	1,917.2	212.3	11.74%	3.72%
Jetstar		Sum	32,513	19,879	–	–
		Average	219.7	134.3	6.07%	22.29%
Air New Zealand	Instagram	Sum	562,956	7,493	–	–
		Average	2,077.3	27.6	8.80%	1.54%
Jetstar		Sum	150,785	3,230	–	–
		Average	484.8	10.4	9.92%	3.93%

Table 3
Train set regression.

			Number of likes		Number of comments	
			With interaction original	With interaction train (70%)	With interaction original	With interaction train (70%)
	Adjusted R Square		0.763	0.769	0.605	0.621
	F		196.808***	141.019***	93.937***	70.071***
	(Constant)		1.731	1.720	−0.498	−0.532
Independent variables	Format		0.258***	0.306***	−0.566***	−0.628***
	Platform		0.250***	0.216***	−0.405***	−0.378***
	Rational		−0.239***	−0.241**	0.260***	0.254***
	Emotional		−0.005	0.003	−0.069*	−0.085*
	Transactional		−0.082*	−0.116**	0.165***	0.163**
Control variables	Content freshness		−0.018	−0.024	−0.229~	−0.180
	Company		−0.408***	−0.406***	0.247***	0.265***
	Scheduling		−0.050*	−0.044~	0.071*	0.065~
	Time lag effect	Like lag	0.209***	0.202***	–	–
		Comment lag	–	–	0.090**	0.062*
	Net sentiment		0.967***	0.832***	−0.789***	−0.737**
	Engagement effect	No. of likes	–	–	0.733***	0.780***
		No. of comments	0.374***	0.393***	–	–
Interactions	Rational _format		0.105**	0.123**	−0.123**	−0.119*
	Rational _platform		0.112***	0.109**	−0.130**	−0.133*
	Emotional _format		−0.055*	−0.069*	0.132***	0.146***
	Emotional _platform		0.029	0.034	−0.004	−0.009
	Transactional _format		0.021	0.020	0.073	0.092
	Transactional _platform		0.069*	0.106*	−0.258***	−0.310***

(Significance level of significant variables: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, ~ $p < 0.1$)

SUR Model

Systems of equations include multiple equations instead of a single equation. Seemingly Unrelated Regressions (SUR) contain only exogenous regressions (Zellner, 1962). The reason that the equations are called seemingly unrelated is that they are only related through the error terms (see Baltagi, 1980). An SUR is an extension of a linear regression that permits correlated errors between equations (Peremans & Van Aelst, 2018). Correlation in error terms between equations with different dependent variables is particularly likely when both equations utilize the same dataset (Engle & Granger, 1987). Further, given the absence of endogeneity of outsourcing in the model, an SUR model is preferable to 3SLS because it does not require instruments, and hence it is likely to yield more precise estimates (Weigelt, 2009). In some conditions, the obtained regression coefficient estimators are at least asymptotically more efficient than those obtained by an equation-by-equation application of least squares (Zellner, 1962). This gain in efficiency can be quite large if “independent” variables in different equations are not highly correlated and if disturbance terms in different equations are highly correlated (Zellner, 1962). In our final model, we have two dependent variables and 19 independent variables (including interaction effects in the full model). The result of the correlation analysis on the normalized version of dependent variables is presented in Table 5.

As can be seen in Table 5, the correlation between the number of likes and number of comments is low. For more investigation, the residual value for each dependent variable for the related regression model and the correlation between the residuals was measured. The result of correlation analysis for the residuals is presented in Table 6.

As the results illustrated in Table 6, there is a significant correlation between the residuals of the No. of comments and

Table 4
Paired sample test for comparing the train dataset estimation and test dataset.

		Paired differences					t	df	Sig. (2-tailed)
		Mean	Std. deviation	Std. error mean	95% confidence interval of the difference				
					Lower	Upper			
Pair 1	Estimated like – Real like	0.01437	0.26673	0.01498	−0.01510	0.04385	0.959	316	0.338
Pair 2	Estimated comment – Real comment	0.00781	0.38088	0.02139	−0.03428	0.04990	0.365	316	0.715

(Significance level of significant variables: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, ~ $p < 0.1$)

Table 5
Correlation analysis between dependent variables.

	Norm comment	Norm likes
Norm comment	1	0.125**
Norm likes	0.125**	1

(Significance level of significant variables: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, ~$p < 0.1$)

Table 6
Pearson correlation between the residuals at the 0.01 level (2-tailed).

	Standardized residual like	Standardized residual comment
Standardized residual like	1	−0.499**
Standardized residual comment	−0.499**	1

(Significance level of significant variables: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, ~$p < 0.1$)

number of likes. Also, the kurtosis value for both residuals was rather high and the test of normality was found significant meaning that we have non-normal residuals (see Appendix 1). We then applied SUR due to the correlation between the residuals of the two dependent variables: likes and comments. Having utilized Breusch-pagon test of SUR, it was confirmed that there is a significant relationship between these two variables. This means there is a meaningful correlation across these two equations (see Appendix 2).

The next step was the cross-equation test. The null hypothesis here was that the effect of a specific single independent variable on the dependent variables in two sets of equations is equal to each other. We needed to see the constraint effect of single at the same time. The results of the cross-equation test are demonstrated in Table 7.

Cross-equation test across different independent variables is the test for the equality of coefficients-for similar independent variable-in both equations. If we cannot reject the null hypothesis, we can impose a cross-equation restriction of equal coefficients and estimates in the SUR model. Drawing on the study of Zellner (1962), we investigated whether independent variables in different equations are correlated. Based on the results of the cross-equation constraint test, we realized that format, platform, rational, transactional, rational-x-format, rational-x-platform, emotional-x-format, and transactional-x-platform have different effects on the dependent variables, and they are not the reason of heteroscedasticity between two dependent variables. For controlling and observing, the effect of non-significant independent variables (emotional, emotional-x-platform, and transactional-x-format), we had to fix each independent variable one by one to be able to compare their effects on the two equations by using SUR (see Shahbaznezhad, 2018). If we encountered new significant results and respected coefficient (for other existing independent variables in the model) or a significant difference between the R-square comparing two separate models, then we could say that variable is the source of endogeneity between two equations.

A summary statistics of the results is presented in Appendices 3 and 4. As can be seen, there is not an outstanding difference for R squared value before and after fixing all the effects. This means that our main OLS model was robust enough that if some independent variables have some similar effects (or be correlated) on two separate regression models, they will not make any strong effect on the robustness of the results of the main initial models. The main effect that it might take our attention is about having a new significant variable after controlling for emotional, emotional-x-platform, and transactional-x-format.

Endogeneity

The third step to assess the validity of the results in this study was the endogeneity test. The main causes of endogeneity are due to having errors in measuring the explanatory variables or it is because of reverse causality (Verbeek, 2008). As for the measurement error, our dataset is considered as secondary data, as such the measurement error is zero. However, there might be some biases in data labeling for which we performed inter-coder reliability to remove it. For reverse causality (the explanatory variable is caused by a dependent variable), we assumed that we do have reverse causality since we use “number of comments” as the independent variable for predicting the number of likes, and the same in reverse. Therefore, we assumed that number of comments is an endogenous variable for the “like” equation. The first step at this stage was to measure the standardized residual for two different equations and see the correlation between them (as error terms) with the dependent and independent variables in the model. The result of correlation analysis presented in Appendix 5) revealed that there was a significant correlation between standardized residual of like equation and like as dependent variable (0.483). In addition, there was a significant correlation between the standardized residual of comment equation and comment as the dependent variable (0.624). However, there is no correlation between the standardized residual of each equation with other independent variables on that equation. To remove the potential endogeneity and test the new model, we performed PLS path modeling (see Benitez,

Table 7
Cross-equation test across different independent variables.

Variable	Chi2	Prob > chi2
Format	52.52	0.0000
Platform	49.31	0.0000
Rational	121.24	0.0000
Emotional	2.80	0.0943
Transactional	18.20	0.0000
Rational_format	19.10	0.0000
Rational_platform	20.53	0.0000
Emotional_format	19.78	0.0000
Emotional_platform	1.15	0.2840
Transactional_format	0.56	0.4560
Transactional_platform	30.87	0.0000

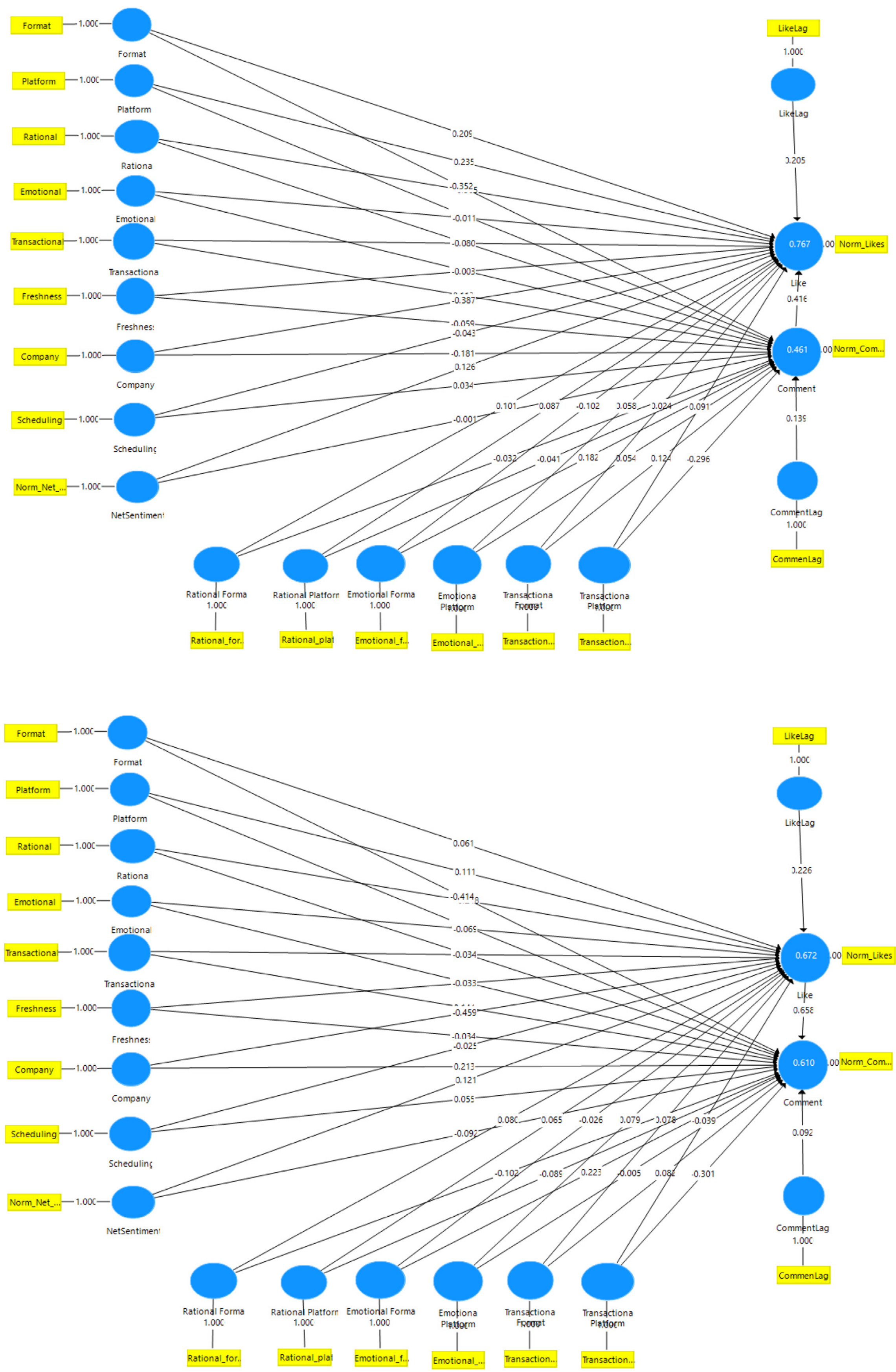

Fig. 2. Path models for Endogeneity Check.

Table 8
The regression result comparison between OLS and Path analysis.

			Number of likes			Number of comments		
			OLS Model	Path Model	P-value after bootstrapping	OLS Model	Path Model	P-value after bootstrapping
	Adjusted R square		0.763	0.763		0.605	0.604	
	F		196.808***			93.937***		
	(Constant)		1.731			−0.498		
Independent variables	Format		0.258***	0.209	** 0.001	−0.566***	−0.414	***0.000
	Platform		0.250***	0.235	*** 0.000	−0.405***	−0.344	*** 0.000
	Rational		−0.239***	−0.305	*** 0.000	0.260***	0.290	*** 0.000
	Emotional		−0.005	−0.011	0.829	−0.069*	−0.109	* 0.017
	Transactional		−0.082*	−0.080	~ 0.089	0.165***	0.144	** 0.001
Controls	Freshness		−0.018	−0.003	0.643	−0.229~	−0.034	* 0.025
	Company		−0.408***	−0.387	*** 0.000	0.247***	0.213	*** 0.000
	Scheduling		−0.050*	−0.043	** 0.001	0.071*	0.055	** 0.008
	Time lag	Like lag	0.209***	0.205	*** 0.000	–	–	–
		Comment lag	–	–	–	0.090**	0.092	*** 0.000
	Engagement effect	No of Likes	–	–	–	0.733***	0.658	*** 0.000
		No of comments	0.374***	0.416	*** 0.000	–	–	–
	Net sentiment		0.967***	0.126	*** 0.000	−0.789***	−0.092	*** 0.000
Interactions	Rational_format		0.105**	0.101	* 0.010	−0.123**	−0.102	* 0.014
	Rational_platform		0.112***	0.087	** 0.001	−0.130**	−0.089	** 0.007
	Emotional_format		−0.055*	−0.102	~ 0.070	0.132***	0.223	*** 0.000
	Emotional_platform		0.029	0.058	0.196	−0.004	−0.005	0.920
	Transactional_format		0.021	0.024	0.647	0.073	0.082	0.152
	Transactional_platform		0.069*	0.091	~ 0.068	−0.258***	−0.301	*** 0.000

Henseler, & Roldán, 2016). The path models are depicted in Fig. 2. The regression result of the path analysis for both dependent variables is shown in Table 8.

As presented in Table 8, the results of the OLS model and path model were consistent. We therefore concluded that the results of this study were valid, through multiple analytical methods.

Regression Analysis

To examine the effect of the independent and covariates on the dependent variables, we used multiple regression with categorical variables (see Long, 1997). The independent variables in this study are the count of four sub-categories content (within each of the three overarching content types) that it can change from 0 to 4. Content freshness was the only covariate that was a scale variable. All grouping variables were binary variables. We used dummy variables for content format (video and photo), company, and platform, as they were nominal variables. Dependent variables in this study, i.e., No. of likes, No. of comments, and net sentiment, were count variables (Cvijikj & Michahelles, 2013). The likes and comments followed a Poisson distribution. In addition, while positiveness and negativeness, as the main components of the net sentiment, followed the poison distribution, net sentiment followed the normal distribution with high kurtosis. One of the assumptions of the linear regression is multivariate normality (Uyanik & Guler, 2013). Considering that the dependent variables were highly skewed and their kurtosis was high and did not follow normal distribution (see Appendix 1), a logarithmic a non-linear transformation by adding 1 to avoid the possibility of taking log of 0 was performed (see Ba & Pavlou, 2002). We also checked for multicollinearity, which indicated no correlation between independent variables in the regression model (see Appendix 2). Moreover, we assessed the outliers by looking at maximum Mahalanobis distance value for each regression model. We checked for homoscedasticity assumption by comparing the regression standardized residual and regression standardized predicted value in a scatter plot. The results showed that there was a flat line for all different regression models. Considering the interaction effects of independent variables and grouping variables in the model, the full regression models for each dependent variables were developed as follow:

$$\begin{aligned} Yij = {} & \alpha_{1j}\text{Informational} + \alpha_{2j}\text{Transformational} \\ & + \alpha_{3j}\text{Transactional} + \alpha_{4j}Format + \alpha_{5j}Platform \\ & + \alpha_{6j}Freshness + \alpha_{7j}Company + \alpha_{8j}Userbase \\ & + \alpha_{9j}Scheduling + \alpha_{10j}Info * Frmt + \alpha_{11j}Inf * Plt \\ & + \alpha_{12j}\text{Transf} * \text{Frmt} + \alpha_{13j}\text{Transf} * \text{Plt} + \alpha_{14j}\text{Trans} \\ & * Plt + \alpha_{15j}\text{Trans} * \text{Frmt} + \varepsilon_{1j} \end{aligned} \tag{1}$$

In this equation, i was used to demonstrate the index for the coefficient of different independent variables, and j was the index for the number of comments or likes.

Table 9 presents the results of regression analysis. In this table, two different regression models for each dependent variable are represented. For each dependent variable, the first model is the model with having the main effects of independent variables, grouping, and control variables. The second model presents the interaction effects of the main independent

Table 9
Multiple regression analysis.

			Number of likes		Number of comments	
			Without interaction effects model	With interaction effects model	Without interaction effects model	With interaction effects model
	Adjusted R Square		0.752	0.763	0.572	0.605
	F		285.099***	196.808***	126.301***	93.937***
	(Constant)		1.593	1.731	−0.369	−0.498
Independent variables	Format		0.263***	0.258***	−0.390***	−0.566***
	Platform		0.399***	0.250***	−0.712***	−0.405***
	Rational		−0.131***	−0.239***	0.146***	0.260***
	Emotional		−0.025*	−0.005	0.017	−0.069*
	Transactional		−0.020	−0.082*	0.071	0.165***
Controls	Freshness		0.022	−0.018	−0.319	−0.229~
	Company		−0.440***	−0.408***	0.281***	0.247***
	Scheduling		−0.051*	−0.050*	0.073	0.071*
	Time lag	Like lag	0.235***	0.209***	–	–
		Comment lag	–	–	0.113***	0.090**
	Net sentiment		0.999***	0.967***	−0.814***	−0.789***
	Engagement effect	No of likes	–	–	0.692***	0.733***
		No of comments	0.352***	0.374***	–	–
Interactions	Rational_format		–	0.105**	–	−0.123**
	Rational_platform		–	0.112***	–	−0.130**
	Emotional_format		–	−0.055*	–	0.132***
	Emotional_platform		–	0.029	–	−0.004
	Transactional_format		–	0.021	–	0.073
	Transactional_platform		–	0.069*	–	−0.258***

(Significance level of significant variables: ***p < 0.001, **p < 0.01, *p < 0.05, ~p < 0.1)

variables and grouping variables. Interaction effects mean that the difference between groups on one treatment variable varies depending on the level of the second treatment variable (Shahbaznezhad, 2018). In the second model, the interaction effects were evaluated with the same criteria as the main effects. When the statistical tests indicate that the interaction is non-significant, this denotes that the effects of the treatments are independent. Independence in factorial designs means that the effect of one treatment (i.e., group differences) is the same for each level of the other treatment(s) and that the main effects can be interpreted directly. If the interactions are not statistically significant, then the main effects can be interpreted directly because the difference between treatments is considered constant across combinations of levels (Hair, Anderson, Babin, & Black, 2010).

Results

Following the analyses presented in the previous section, we now assess the integrity of each proposed research hypotheses.

The output presented within Table 8 provides strong evidence to support H1, indicating that the format of content, i.e., video (H1a) or photo (H1b) (coded as 0 and 1 accordingly) has a significant effect on different types of engagement behavior. As proposed in H1a, video format posts encourage users to actively engage on fan page by sharing their opinion and comments toward firms' posts, while photo formatted content stimulates passive users' engagement through liking behavior. These media types represent a different level of media richness, also commonly referred to as vividness of online content (Daft & Lengel, 1986). Moreover, different media types exhibit different levels of interactivity, expressed through the degree to which users can influence the form and content of the media environment (Steuer, 1992). Previous studies in the field of online advertisements (e.g., Fortin & Dholakia, 2005; Lohtia et al., 2003) found out the existence of the positive effect of vividness over the effectiveness of the online advertisement, measured by the level of interaction with the online ad. While our research findings are generally consistent with previous work, verifying the content format significantly affects engagement behavior, it is challenged by some previous work on the type of users' engagement. For instance, Sabate et al. (2014) argue that photos significantly increase passive and active brand post engagement, whereas videos promote more passive engagement behavior. They argue that images are easier to digest, and, in a few seconds, users can write a short comment about the feelings/opinions that the picture is invoked on them. However, the process of commenting requires users to dedicate more time to first assimilate the content and second publicly assess it by writing an opinion (Shahbaznezhad, 2018). Undoubtedly, commenting requires an additional effort compared to liking which requires only one click. In the same way, Cvijikj and Michahelles (2013) found that Facebook posts that have a higher level of interactivity, i.e., videos, lead to a lower level of engagement.

Our results also provide sufficient evidence to support H2, revealing that users' behavior on the firms' fan page is influenced by the social media platform environment. As mentioned earlier, we selected two popular social media platforms—Facebook and Instagram (coded as 0 and 1 accordingly). The findings confirm that firms' fan page users on Instagram tend to “like” more (passive engagement) than generating comments (active engagement). In reverse, commenting on Facebook has shown as a more popular engagement behavior. In other words, Facebook provides an environment that provokes users to have active engagement behavior and write more comments than Instagram. Instagram has an app-based design with a very aesthetic platform (double tap for liking) (Sheldon & Bryant, 2016), and it is evident that users tend to “like” more on this platform than for the same posts on Facebook. The results also showed that by imposing a positive vibe to users (sentiment of posts), Instagram stimulates users' interests through more positive comments compared to Facebook, which has a more rational environment.

Having assessed the first two hypotheses, we now move to the H3 to H5 which investigate the moderating effect of content context on the relationship between different content types and users' engagement behavior. First, we posited the extent to which the effect of social media content on social media engagement behavior is moderated by the format of the content (H3a, H4a, and H5a). We expected differences in this relationship to unfold across the three types of content studied (rational, emotional, and transactional). Our findings reveal that rational content, presented in photo format, significantly stimulates more likes than comments. This means that rational content is sensitive to the format of the content (H3a). In contrast, we could not find full supporting evidence on emotional content to conform H4a. While emotional content has a significantly negative effect on liking behavior, the interaction effect of this content type with content format demonstrates no significant link to users' liking behavior. This means that the content format plays no role in the extent of emotional content to stimulate users' engagement behavior. However, the results showed that emotional content has a significantly negative effect on commenting behavior, once we consider the interaction effect of the content format. This means that users are not interested in writing comments on emotional content, unless it is not presented in the specific format. Moreover, our findings suggest that if emotional content is presented in the photo format, there would be a reverse effect on liking behavior, whereas emotional content in the video format stimulates an increase in active engagement (commenting). Thus, it can be concluded that emotional content may be best suited to a higher media richness format (video), as it can convey greater levels of emotional stimuli such as music and movement compared to a photo post.

Finally, it was revealed that transactional content and the content format do not have any significant interactions. This means that the impact of transactional content on users' engagement behavior is format independent. As such, H5a was rejected.

Concerning the moderating role of the platform (as hypothesized in H3b, H4b, and H5b), we found that rational content on Instagram significantly gets more likes than comments. This confirms that rational content is sensitive to the platform type (H3b). In contrast, emotional content and the platform which content is presented on, do not have any significant interactions. This means that the emotional content effect on user engagement behavior is platform-independent. As such, we are unable to provide sufficient evidence to support H4a. Moving to transactional content, the results supportH5b, revealing the significant moderating impact of the platform on users' engagement. It was found out that transactional content presented on Instagram attracts more likes, while it threatens comments. In other words, presenting transactional posts on Instagram may not be an effective tool for stimulating users' commenting behavior, while it promotes liking. It is worth adding that transactional content did not have any significant effect on liking or commenting behavior in the original model, however, once the interaction of content type with the platform was added, a significantly positive impact on liking and commenting behavior was discovered.

Discussion and Implications

Today's business environment has become more interactive, where customers are continuously are engaged with offerings and activities of firms (Dolan, Conduit, et al., 2019). Customers engage for various reasons through various objects, such as product or service offerings (Brodie et al., 2011), media (Calder et al., 2009), activities, and events (Vivek et al., 2012). Although recent research has explored both the antecedents and consequences of customer engagement (Gambetti, Graffigna, & Biraghi, 2012; Leckie, Nyadzayo, & Johnson, 2016; Van Doorn et al., 2010), the extant literature still lacks a systematically empirical study to assess the theoretical foundation of customer engagement in response to social media marketing practices (Sashi, 2012). This allows for scrutinizing the social media behavioral response of customers to organizational communications such as brand posts on Facebook (Dolan, Seo, & Kemper, 2019). While much of the literature identifies individual-related factors as antecedents of customer engagement, few studies (e.g., Cvijikj & Michahelles, 2013; Dolan, Conduit, et al., 2019; Lee et al., 2018) have studied the impact of social media content strategy on engagement behavior). Thus, a more in-depth analysis of the impact of social media content posted by firms is warranted. To the best of our knowledge, previous literature is yet to identify how the various types of content (e.g. rational compared to emotional, and transaction) would be more or less suited to certain platforms (e.g. Instagram or Facebook), in terms of facilitating social media engagement behavior, as we have investigated within this paper. As such, this study makes several preliminary contributions to engagement and social media literature, offering areas for further exploration within this area.

First, this research endeavored to acknowledge the important role of the type of platform (Facebook vs. Instagram) in facilitating social media engagement behavior. Previous studies (e.g., Dolan, Seo, & Kemper, 2019) have focused on singular platforms of inquiry. The results of this study demonstrate that Instagram users (fans) appear to be more passively engaged, compared to fans on Facebook who tend to demonstrate greater active behavior in the form of commenting. This could be because Facebook may be commonly used on a desktop vs. mobile app device allowing users ease of typing comments compared to on a phone. For managers, if an objective of social media content is to gather rich feedback through comments and discussion, this finding suggests that Facebook may be the superior platform. Further research is needed however to fully encapsulate the type of users across platforms, and the effect this may have on their engagement.

Second, our study offers preliminary insights into our understanding of the role of the content format through our investigation of how this variable may moderate the effectiveness of specific types of content on social media engagement behavior. Exploring these relationships to the detailed level of individual content types is crucial for managers as they can understand how and why the selection of the most suitable format to post their content will vary depending on the specific type of content that is being communicated (e.g. rational, emotional, or transactional). To illustrate, our findings empirically demonstrate that when posting rational content, using the "photo" format will generate significantly more likes than comments. This may be good for boosting "virality" of a post, yet it may not be helpful if the objective is to seek comments or conversational feedback. When posting emotional content, we show that using the video format will stimulate active engagement from users (in the form of comments). Tourism firms who may wish to communicate a highly emotional message, and achieve active engagement (comments), should, therefore, utilize videos in their content.

Third, the results of our paper identified a unique and novel finding regarding a significantly positive effect between different patterns of user engagement behavior on posts within the firm's fan pages. It was identified that the number of comments on a post and the sentiment of those comments significantly stimulate the number of likes on the post. For managers, this identifies the importance of generating positive, active engagement in the form of comments to enhance the ongoing virality of the post in the form of likes. Interestingly, we also identified a significant negative effect between the net sentiment and number of comments for the firms' posts. This indicates that fans tend to express their opinion and write more comments with a negative sentiment, than positive. Managers, as well as scholars, need to further understand the implications of negative comments and word-of-mouth on social media platforms, as this could be potentially damaging to a brand.

Limitations and Directions for Future Research

This paper examined the literature of social media content and user engagement to develop an empirical model and related hypotheses which draw upon the theoretical foundations of Media Richness. This framework proposes three main social media content types; rational, emotional, and transactional, and explores how their effects of active and passive engagement behavior are altered by the content context, namely the format and platform. Using a dataset of 1,038 social media posts and 1,336,741 and 95,996 fan likes and comments, respectively based on two platforms of Facebook and Instagram, we demonstrate significant relationships as proposed in the framework. The results of this research demonstrate that the effectiveness of rational, emotional, and transactional social media content on social media engagement does significantly vary depending on the format of the content (photo vs. video), as well as the platform on which the content is presented (Facebook or Instagram).

The dataset utilized for this study is, however, limited to publicly accessible information from the social media pages of the respective companies. As such, important variables including advertising spending (e.g., investment in sponsored posts) and the total number of impressions (views of posts) compared to the level of engagement (e.g., likes, shares, and comments) are not included within this study. Future scholars should endeavor to capture such data to confirm and extend our preliminary findings. Future research could then capture important information, such as how advertising spending, on video production and placement, may lead to higher impressions, and thus higher engagement. Further, a more complex dataset of social media advertising and engagement may allow access to important information, such as targeting criteria used for social media posts. To achieve this, scholars could collaborate with companies to access their social media data (e.g., Facebook or Instagram Insights) and pair this with data on their advertising spending. Scholars could then also compare companies from the same industry who have varying levels of social media advertising spending, and varying content strategies, to assess their impact on performance in terms of engagement. Our dataset is also limited to the viewable dependent variables of likes and comments. Researchers should endeavor to extend on this to include important metrics such as "click-through rates," as this is likely to be an important metric among marketing managers, especially for those seeking increased website traffic.

Lastly, as our dataset is secondary, we are unable to consider and research the characteristics of users who are engaging with posts, e.g., demographic factors, and so on. As per typical survey research, the inclusion of such data would allow the researchers to control for many sources of bias. The lack of this information means there is likely a self-selection bias in the type of consumers who use Facebook vs. Instagram, or use both platforms. For example, recent statistics show that in 2020, 74% of Facebook users are "high-income earners" (USD 75,000 per annum), compared to 42% for Instagram (Aboulhosn, 2020). Further, users aged 65 and over are the fastest-growing group of users on Facebook, while gen X'ers have reduced their Facebook use (Aboulhosn, 2020). These factors, and many more, provide an important narrative around understanding the type of users engaging across platforms, and this information must be included in future studies to ensure a more robust understanding of the nature of cross-platform use and engagement. To do so, future researchers may consider an experimental design in which they work with a company to manipulate their social media strategy and spending across platforms for various target audiences over some time.

This research was conducted with social media data from a single industry-Airlines. Future research is required in a broader range of industries and product categories which would provide more insights on how social media content should be used to generate engagement. Future scholars would then be able to identify or investigate how industry, product, and brand characteristics play a role in generating online engagement. Another important note for future scholars is to adopt a deeper conceptualization of engagement. In this study, we focus solely on engagement behaviors, limited to actions within social media platforms (liking and commenting). Further research in this area may want to investigate other forms of online engagement, as well as other dimensions of engagement (e.g., cognitive and affective). Finally, scholars need to also look toward the consequences of achieving social media engagement behavior. This study provides empirical strategic evidence and guidelines for generating engagement in social media; yet further research is needed to consider the benefits of such engagement, for example, brand-related outcomes such as brand equity, purchase intention, offline word-of-mouth, and customer satisfaction. Such research would provide a more holistic picture of the important nature of understanding how, and why, generating online engagement is critical.

Acknowledgements

We thank Associate Professor Arvind Tripathi (The University of Auckland) for supporting this research financially and useful discussions. Also we thank Professor Ananth Srinivasan (The University of Auckland) for his useful guidance in the methodology section.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.intmar.2020.05.001.

References

Aaker, D. A., Stayman, D. M., & Hagerty, M. R. (1986). Warmth in advertising: Measurement, impact, and sequence effects. *Journal of Consumer Research, 12*(4), 365–381.

Aboulhosn, S. (2020). 18 Facebook statistics every marketer should know in 2020. Available at https://sproutsocial.com/insights/facebook-stats-for-marketers/ (Accessed 12 March 2020).

Alhabash, S., McAlister, A. R., Hagerstrom, A., Quilliam, E. T., Rifon, N. J., & Richards, J. I. (2013). Between likes and shares: Effects of emotional appeal and virality on the persuasiveness of anticyberbullying messages on Facebook. *Cyberpsychology, Behavior and Social Networking, 16*(3), 175–182.

Ashley, C., & Tuten, T. (2015). Creative strategies in social media marketing: An exploratory study of branded social content and consumer engagement. *Psychology & Marketing, 32*(1), 15–27.

Ba, S., & Pavlou, P. A. (2002). Evidence of the effect of trust building technology in electronic markets: Price premiums and buyer behavior. *MIS Quarterly, 26*(3), 243–268.

Baltagi, B. H. (1980). On seemingly unrelated regressions with error components. *Econometrica, 48*(6), 1547–1551.

Baron, P., & Corbin, L. (2012). Student engagement: Rhetoric and reality. *Higher Education Research and Development, 31*(6), 759–772.

Benitez, J., Henseler, J., & Roldán, J. (2016). How to address endogeneity in partial least squares path modeling. *22th Americas conference on information systems (AMCIS 2016), 11–14 August, San Diego, US.*

Brodie, R. J., Hollebeek, L., Jurić, B., & Ilić, A. (2011). Customer engagement conceptual domain, fundamental popositions, and implications for research. *Journal of Service Research, 14*(3), 252–271.

Brodie, R. J., Ilic, A., Juric, B., & Hollebeek, L. (2013). Consumer engagement in a virtual brand community: An exploratory analysis. *Journal of Business Research, 66*(1), 105–114.

Calder, B. J., Malthouse, E. C., & Schaedel, U. (2009). An experimental study of the relationship between online engagement and advertising effectiveness. *Journal of Interactive Marketing, 23*(4), 321–331.

Casaló, L., Flavián, C., & Guinalíu, M. (2007). The impact of participation in virtual brand communities on consumer trust and loyalty: The case of free software. *Online Information Review, 31*(6), 775–792.

Cheung, C. M, Chiu, P. Y, & Lee, M. K (2011). Online social networks: Why do students use Facebook? *Computers in Human Behavior, 27*(4), 1337–1343.

Coelho, R. L. F., Oliveira, D. S. d., & Almeida, M. I. S. d. (2016). Does social media matter for post typology? Impact of post content on Facebook and Instagram metrics. *Online Information Review, 40*(4), 458–471.

Coulter, K. S., Gummerus, J., Liljander, V., Weman, E., & Pihlström, M. (2012). Customer engagement in a Facebook brand community. *Management Research Review, 35*(9), 857–877.

Cvijikj, I. P., & Michahelles, F. (2013). Online engagement factors on Facebook brand pages. *Social Network Analysis and Mining, 3*(4), 843–861.

Daft, R. L., & Lengel, R. H. (1986). Organizational information requirements, media richness and structural design. *Management Science, 32*(5), 513–644.

De Vries, L., Gensler, S., & Leeflang, P. S. (2012). Popularity of brand posts on brand fan pages: An investigation of the effects of social media marketing. *Journal of Interactive Marketing, 26*(2), 83–91.

Dijkmans, C., Kerkhof, P., & Beukeboom, C. J. (2015). A stage to engage: Social media use and corporate reputation. *Toursim Management, 47*(4), 58–67.

Dolan, R., Conduit, J., Fahy, J., Brodie, R. J., Hollebeek, L. D., & Conduit, J. (2016). Social media engagement: A construct of positively and negatively valenced engagement behaviour. In R.J. Brodie, L.D. Hollebeek & J. Conduit (Eds.) *Customer Engagement: Contemporary Issues and Challenges* (pp. 102–102). London, UK: Routledge.

Dolan, R., Conduit, J., Frethey-Bentham, C., Fahy, J., & Goodman, S. (2019). Social media engagement behavior: A framework for engaging customers through social media content. *European Journal of Marketing*, https://doi.org/10.1108/EJM-03-2017-0182.

Dolan, R., Seo, Y., & Kemper, J. (2019). Complaining practices on social media in tourism: A value co-creation andco-destruction perspective. *Tourism Management, 73*(8), 35–45.

Enge, E. (2019). Where is the Mobile vs. Desktop Story Going. Retrieved from https://www.perficientdigital.com/insights/our-research/mobile-vs-desktop-usage-study (Accessed 12 March 2020).

Engle, R. F., & Granger, C. W. J. (1987). Co-integration and error correction: Representation, estimation, and testing. *Econometrica, 55*(2), 251–276.

Fortin, D. R., & Dholakia, R. R. (2005). Interactivity and vividness effects on social presence and involvement with a web-based advertisement. *Journal of Business Research, 58*(3), 387–396.

Füller, J., Bartl, M., Ernst, H., & Mühlbacher, H. (2006). Community based innovation: How to integrate members of virtual communities into new product development. *Electronic Commerce Research, 6*(1), 57–73.

Gambetti, R. C., Graffigna, G., & Biraghi, S. (2012). The grounded theory approach to consumer-brand engagement. *International Journal of Market Research, 54*(5), 659–687.

Gavilanes, J. M., Flatten, T. C., & Brettel, M. (2018). Content strategies for digital consumer engagement in social networks: Why advertising is an antecedent of engagement. *Journal of Advertising, 47*(1), 4–23.

Globalwebindex (2019). The Latest Social Media Trends to Know in 2019. Retrieved from https://www.globalwebindex.com/reports/social (Accessed 20 July 2019).

Gummerus, J., Liljander, V., Weman, E., & Pihlström, M. (2012). Customer engagement in a Facebook brand community. *Management Research Review, 35*(9), 857–877.

Hair, J. F., Anderson, R. E., Babin, B. J., & Black, W. C. (2010). *Multivariate data analysis: A global perspective*. Upper Saddle River, NJ: Pearson.

Hallberg, U. E., & Schaufeli, W. B. (2006). "Same same" but different? Can work engagement be discriminated from job involvement and organizational commitment? *European Psychologist, 11*(2), 119–127.

Hallock, W., Roggeveen, A., & Crittenden, V. (2019). Firm-level perspectives on social media engagement: An exploratorystudy. *Qualitative Market Research: An International Journal*, https://doi.org/10.1108/QMR-01-2017-0025.

Harrigan, P., Evers, U., Miles, M., & Daly, T. (2017). Customer engagement with tourismsocial media brands. *Tourism Management, 59*(4), 597–609.

Hoffman, D. L., & Fodor, M. (2010). Can you measure the ROI of your social media marketing? *MIT Sloan Management Review, 52*(1), 41–49.

Hollebeek, L., & Chen, T. (2014). Exploring positively-versus negatively-valenced brand engagement: A conceptual model. *Journal of Product and Brand Management, 23*(1), 62–74.

Hollebeek, L., Glynn, M. S., & Brodie, R. J. (2014). Consumer brand engagement in social media: Conceptualization, scale development and validation. *Journal of Interactive Marketing, 28*(2), 149–165.

Hollebeek, L. D. (2011). Demystifying customer brand engagement: Exploring the loyalty nexus. *Journal of Marketing Management, 27*(7–8), 785–807.

Kanuri, V. K., Chen, Y., & Sridhar, S. (2018). Scheduling content on social media: Theory, evidence, and application. *Journal of Marketing, 82*(6), 89–108.

Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of social media. *Business Horizons, 53*(1), 59–68.

Khoros (2020). The 2020 Social Media Demographics Guide. Retrieved from https://khoros.com/resources/social-media-demographics-guide Accessed 12 March 2020.

Kim, D. H., Spiller, L., & Hettche, M. (2015). Analyzing media types and content orientations in Facebook for global brands. *Journal of Research in Interactive Marketing, 9*(1), 4–30.

King, R. C., & Xia, W. (1997). Media appropriateness: Effects of experience on communication media choice. *Decision Sciences, 28*(4), 877–910.

Krippendorff, K. (2013). *Content Analysis: An Introduction to Its Methodology*. London, UK: Sage Publishing Ltd.

Leckie, C., Nyadzayo, M. W., & Johnson, L. W. (2016). Antecedents of consumer brand engagement and brand loyalty. *Journal of Marketing Management, 32*(5–6), 558–578.

Lee, D., Hosanagar, K., & Nair, H. (2018). Advertising content and consumer engagementon social media: Evidence from Facebook. *Management Science, 64*(11), 4967–5460.

Li, M., Dong, Z. Y., & Chen, X. (2012). Factors influencing consumption experience of mobilecommerce: A study from experiential view. *Internet Research, 22*(2), 120–141.

Li, W. S., Po, O., Hsiung, W. P., Candan, K. S., & Agrawal, D. (2003). Freshness-driven adaptive caching for dynamic content web sites. *Data and Knowledge Engineering, 47*(2), 69–296.

Liu, B. (2012). Sentiment analysis and opinion mining. *Synthesis Lectures on Human Language Technologies, 5*(1), 1–167.

Liu, S. H., Liao, H. L., & Pratt, J. A. (2009). Impact of media richness and flow on e-learning technology acceptance. *Computers and Education, 52*(3), 599–607.

Liu, S. S., & Stout, P. A. (1987). Effects of message modality and appeal on advertising acceptance. *Psychology and Marketing, 4*(3), 167–187.

Liu, X., Burns, A. C., & Hou, Y. (2017). An investigation of brand-related user-generated content on Twitter. *Journal of Advertising, 46*(2), 236–247.

Liu-Thompkins, Y. (2012). Seeding viral content: The role of message and network factors. *Journal of Advertising Research, 52*(4), 465–478.

Lohtia, R., Donthu, N, & Hershberger, E. K. (2003). The impact of content and design elements on banner advertising click-through rates. *Journal of Advertising Research, 43*(4), 410–418.

Long, J. S. (1997). *Regression Models for Categorical and Limited Dependent Variables*. London, UK: SAGE Publications.

Luo, Q., & Zhong, D. (2015). Using social network analysis to explain communicationcharacteristics of travel-related electronic word-of-mouth on social networking sites. *Tourism Management, 46*(2), 274–282.

Malthouse, E. C., Calder, B. J., & Vandenbosch, M. (2016). Evidence that user-generated content that produces engagement increases purchase behaviours. *Journal of Marketing Management, 32*(5–6), 427–444.

Malthouse, E. C., Haenlein, M., Skiera, B., Wege, E., & Zhang, M. (2013). Managing customer relationships in the social media era: Introducing the social CRM house. *Journal of Interactive Marketing, 27*(4), 270–280.

Moro, S., Rita, P., & Vala, B. (2016). Predicting social media performance metrics and evaluation of the impact on brand building: A data mining approach. *Journal of Business Research, 69*(9), 3341–3351.

Muntinga, D. G., Moorman, M., & Smit, E. G. (2011). Introducing cobras. *International Journal of Advertising, 30*(1), 13–46.

Nelson-Field, K., Riebe, E., & Sharp, B. (2012). What's not to "like?" Can a Facebook fan base give a brand the advertising reach it needs? *Journal of Advertising Research, 52*(2), 262–269.

O'Brien, H. L., & Toms, E. G. (2008). What is user engagement? A conceptual framework for defining user engagement with technology. *Journal of the American Society for Information Science and Technology, 59*(6), 938–955.

Okazaki, S., Rubio, N., & Campo, S. (2014). Gossip in social networking sites: Why people chitchat about ad campaigns. *International Journal of Market Research, 56*(3), 49–72.

Peremans, K., & Van Aelst, S. (2018). Robust inference for seemingly unrelated regression models. *Journal of Multivariate Analysis, 167*(9), 212–224.

Peters, K., Chen, Y., Kaplan, A. M., Ognibeni, B., & Pauwels, K. (2013). Social media metrics: A framework and guidelines for managing social media. *Journal of Interactive Marketing, 27*(4), 281–298.

Phillips, B. J., Miller, J., & McQuarrie, E. F. (2014). Dreaming out loud on Pinterest: New forms of indirect persuasion. *International Journal of Advertising, 33*(4), 633–655.

Preece, J., Nonnecke, B., & Andrews, D. (2004). The top five reasons for lurking: Improving community experiences for everyone. *Computers in Human Behavior, 20*(2), 201–223.

PwC (2019). IAB Internet Advertising Revenue Report: 2018 Full Year Results. available at https://www.iab.com/wp-content/uploads/2019/05/Full-Year-2018-IAB-Internet-AdvertisingRevenue-Report.pdf (accessed 05 May 2020).

Quach, S., & Thaichon, P. (2017). From connoisseur luxury to mass luxury: Value co-creation and co-destruction in the online environment. *Journal of Business Research, 81*(12), 163–172.

Raney, A. A, Arpan, L. M, Pashupati, K., & Brill, D. A (2003). At the movies, on the web: An investigation of the effects of entertaining and interactive web content on site and brand evaluations. *Journal of Interactive Marketing, 17*(4), 38–53.

Riffe, D., Lacy, S., & Fico, F. (2014). *Analyzing Media Messages: Using Quantitative Content Analysis in Research*. London, UK: Routledge.

Rosenkrans, G. (2009). The creativeness and effectiveness of online interactive rich media advertising. *Journal of Interactive Advertising, 9*(2), 18–31.

Rust, R. T., & Cooil, B. (1994). Reliability measures for qualitative data: Theory and implications. *Journal of Marketing Research, 31*(1), 1–14.

Sabate, F., Berbegal-Mirabent, J., Cañabate, A., & Lebherz, P. R. (2014). Factors influencing popularity of branded content in Facebook fan pages. *European Management Journal, 32*(6), 1001–1011.

Saks, A. M. (2006). Antecedents and consequences of employee engagement. *Journal of Managerial Psychology, 21*(7), 600–619.

Sashi, C. (2012). Customer engagement, buyer-seller relationships, and social media. *Management Decision, 50*(2), 253–272.

Shahbaznezhad, H. (2018). *Customer and firm interaction on social media platforms*. A PhD thesis Submitted at the University of Auckland, New Zealand (unpublished).

Shaw, R.-S., Chen, C. C., Harris, A. L., & Huang, H. (2009). The impact of information richness on information security awareness training effectiveness. *Computers and Education, 52*(1), 92–100.

Sheldon, P., & Bryant, K. (2016). Instagram: Motives for its use and relationship to narcissism andcontextual age. *Computers in Human Behavior*, 89–97 58:5.

Shu, M., & Scott, N. (2014). Influence of social media on Chinese students' choice of an overseas study destination: An information adoption model perspective. *Journal of Travel and Tourism Marketing, 31*(2), 286–302.

Sook Kwon, E., Kim, E., Sung, Y., & Yun Yoo, C. (2014). Brand followers: Consumer motivation and attitude towards brand communications on Twitter. *International Journal of Advertising, 33*(4), 657–680.

Statista (2019). Most popular social networks worldwide as of April 2019, ranked by number of active users (in millions). Avaialbe at https://www.

statista.com/statistics/264810/number-of-monthly-active-facebook-users-worldwide/ (Accessed 20 July 2019).

Steuer, J. (1992). Defining virtual reality: Dimensions determining telepresence. *Journal of Communication, 42*(2), 73–93.

Swani, K., Milne, G., and P. Brown, B. 2013. "Spreading the word through likes on Facebook: Evaluating the message strategy effectiveness of fortune 500 companies," Journal of Research in Interactive Marketing (7:4), pp. 269–294.

Tafesse, W. (2015). Content strategies and audience response on Facebook brand pages. *Marketing Intelligence and Planning, 33*(6), 927–943.

Tafesse, W. (2016). An experiential model of consumer engagement in social media. *Journal of Product and Brand Management, 25*(5), 424–434.

Taylor, D. G, Lewin, J. E, & Strutton, D (2011). Friends, fans, and followers: Do ads work on social networks? *Journal of Advertising Research, 51*(1), 258–275.

Trevino, L. K., Lengel, R. H., & Daft, R. L. (1987). Media symbolism, media richness, and media choice in organizations: A symbolic interactionist perspective. *Communication Research, 14*(5), 553–574.

Tseng, F. C., Cheng, T. C. E., Li, K., & Teng, C. I. (2017). How does media richness contribute to customer loyalty to mobile instant messaging? *Internet Research, 27*(3), 520–537.

Uyanik, G. K., & Guler, N. (2013). A study on multiple regression analysis. *Procedia- Social and Behavioral Sciences, 106*(12), 234–240.

Van Doorn, J., Lemon, K. N., Mittal, V., Nass, S., Pick, D., & Pirner, P., et al (2010). Customer engagement behavior: Theoretical foundations and research directions. *Journal of Service Research, 13*(3), 253–266.

Van Noort, G., Antheunis, M. L., & Verlegh, P. W. L. (2014). Enhancing the effects of social network site marketing campaigns. *International Journal of Advertising, 33*(2), 235–252.

Verbeek, M. (2008). *A Guide to Modern Econometrics*. Chicheste, UK: John Wiley and Sons Ltd.

Vivek, S., Beatty, S., & Morgan, R. (2012). Customer engagement: Exploring customer relationships beyond purchase. *Journal of Marketing Theory and Practice, 20*(2), 122–146.

Voorveld, H. A., Van Noort, G., Muntinga, D. G., & Bronner, F. (2018). Engagement with social media and social media advertising: The differentiating role of platform type. *Journal of Advertising, 47*(1), 38–54.

Walther, J. B., DeAndrea, D., Kim, J., & Anthony, J. C. (2010). The influence of online comments on perceptions of antimarijuana public service announcements on YouTube. *Human Communication Research, 36*(4), 469–492.

Weigelt, C. (2009). The impact of outsourcing new technologies on integrative capabilities and performance. *Strategic Management Journal, 30*(6), 595–616.

Wirtz, J., Aksoy, L., Van Riel, A., Kandampully, J., den Ambtman, A., & Bloemer, J., et al (2013). Managing brands and customer engagement in online brand communities. *Journal of Service Management, 24*(3), 223–244.

Zellner, A. (1962). An efficient method of estimating seemingly unrelated regressions and tests for aggregation bias. *Journal of the American Statistical Association, 57*(298), 348–368.

Zeng, B., & Gerritsen, R. (2014). What do we know about social media in tourism? An oreview. *Tourism Management Perspectives*(10:4), 27–36.

Zielke, S. (2011). Integrating emotions in the analysis of retail price images. *Psychology and Marketing, 28*(4), 330–359.