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Article (Accepted Version)

Shahbaznezhad, Hamidreza, Dolan, Rebecca and Rashidirad, Mona (2021) The role of social media content format and platform in users' engagement behavior. *Journal of Interactive Marketing*, 53. pp. 47-65. ISSN 1094-9968

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The role of social media content format and platform in users' engagement behavior

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) 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

1. Introduction

Due to the on-going 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 and 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 1000 million in June 2018 (Statista, 2019). Correspondingly, social media content directed at customers continues to proliferate as customers' digital spending increases (Malthouse, Calder and 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 and Nair, 2018).

Previous studies (e.g., Gavilanes, Flatten and 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 and Tuten, 2015; Dolan et al., 2016 a,b), or offered a limited conceptualization of social media engagement behavior, mainly through numbers of likes, shares or comments (e.g., Cvijikj and Michahelles, 2013, De Vries, Gensler and Leeflang, 2012). Our understanding of social media content design was also limited, with earlier scholars using broadly defined and limited content types, such as informational vs. entertaining (De Vries, Gensler and Leeflang, 2012) and employing a singular social media platform to test social media engagement, e.g., Facebook, or Instagram (e.g., Kim, Spiller and Hettche, 2015; Lee, Hosanagar and Nair, 2018; Gavilanes, Flatten and Brettel, 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 et al., 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.

2. Literature review

2.1. 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, Hosanagar and Nair, 2018), and co-creators of content through their online interactions and behaviors (Dolan 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 (Muntinga, Moorman, and Smit, 2011; Hallock, Roggeveen and Crittenden, 2019). 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) (Muntinga, Moorman, and Smit, 2011; Malthouse et al., 2013).

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 et al., 2013). Customers' engagement has been studied in many fields, including psychology (e.g., Hallberg and Schaufeli, 2006), education (e.g., Baron and Corbin, 2012) management (e.g., Saks, 2006), marketing (e.g., Hollebeek, 2011; Van Doorn et al., 2010) and Information systems (e.g., O'Brien and 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 and 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 et al., 2011), activities and events (e.g., Vivek et al., 2012), and media (e.g., Calder, Malthouse and Schaedel, 2009). Some (e.g., Malthouse et al., 2013; Muntinga, Moorman, and Smit, 2011) recognized the properties of engagement, such as intensity, and examined its various aspects and antecedents (see also De Vries, Gensler and Leeflang, 2012; Gummerus et al., 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, Malthouse and Schaedel, 2009; Coulter et al., 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., 2016a; Van Doorn et al., 2010). According to Dolan et al., (2016a), there are six types of social media engagement behavior on fan pages: creating, contributing, destructing (known as active engagement behaviors) and 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 et al. (2016a) suggest two typologies that encompass the seven behavioral groups (referred above). As they argue, it can be passive (low) or active (high) and also engagement can be 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 and 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 and Guinalú, 2007). There are different metrics to measure the intensity of passiveness or activeness of social media engagement (see Peters et al., 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, et al., 2016a). 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 and Chen, 2014).

2.2 Social media content types and users’ engagement

Drawing on the 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.

---Insert Table 1 about here---

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 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 and Hagerty, 1986; Liu and 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 et al., (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, Milne and P. Brown (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 et al., 2006). Some users expect to gain a reward, such as a monetary incentive, job-related benefit or personal needs (Muntinga, Moorman, and Smit, 2011). The work of Cvijikj and Michahelles (2013) and Dolan et al., (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 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 et al., 2019).

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 focussed 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.

3. Conceptual Model and Hypotheses

3.1 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., Liu, Liao and Pratt, 2009; Kaplan and Haenlein, 2010; Tseng et al., 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 and Daft, 1987). The underlying message of this theory is that communication efficiency can be improved by matching media to users' information needs (Daft and 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 et al., 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 and 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 and 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 (De Vries, Gensler and Leeflang, 2012; Cvijikj and Michahelles, 2013). 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).

3.2 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, Spiller and Hettche (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 et al. (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 and Lengel, 1986), and consistent with some prior research (e.g., De Vries, Gensler and Leeflang, 2012; Cvijikj and Michahelles, 2013; Moro, Rita and 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 7 different social media accounts on different platforms. Most previous research in this field, however, has often focussed on either social media in general (e.g., Muntinga, Moorman, and Smit, 2011; Okazaki, Rubio, and Campo, 2014; Van Noort, Antheunis, and Verlegh, 2014) or only one specific social media platform, such as Facebook (e.g., Nelson-Field, Riebe and Sharp, 2012), YouTube (e.g., Liu-Thompkins, 2012; Walther et al., 2010), Twitter (e.g., Liu, Burns, and Hou, 2017; Sook Kwon et al., 2014;), or Pinterest (Phillips, Miller and 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 behaviour to emerge across platforms, as the user experience, and devices may be different. To begin with, while Facebook users mostly (96 percent) access Facebook through a mobile device via the Facebook App, 25 percent 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, 2017). 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 focussed 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 out 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 Figure 1.

---Insert Figure 1 about here---

4. Methodology

4.1 Research context

Social media has significantly changed the tourism industry, switching customers' role from passive to active users (Quach and 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 (Zeng and Gerritsen, 2014; Dolan, Seo and Kemper, 2019). Although tourism research in social media context is still in the early stages, scholars (e.g., Shu and Scott, 2014; Luo and Zhong, 2015) 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, et al., 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 are highly sensitive to customers' views/complains (Dolan, Seo and 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 and 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.

4.2 Sampling and data collection

The data of this study were collected from two Pacific airlines, i.e., Air New Zealand and Jetstar Australian. Data were captured across 12 months, including all posts made and their corresponding engagement metrics of likes and comments. The final data set contained 1038 social media posts, 1,336,741 likes and 95,996 comments. Of 1038 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 x 2 platforms), allowing a systemic analysis of brand post strategy and liking/commenting engagement behavior across and between brands and platforms.

4.3 Operationalisation 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 Figure 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 and Fodor, 2010).

4.3.1 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 and Fico, 2014) in addition to being relevant to the research questions. Accordingly, the measures selected for each variable matched the conceptualisations

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 data set 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 subcategory 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 4 subcategories, although the maximum number of content items that any post had was 4; this means that content levels were coded from 0–4. 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).

4.3.2 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.

4.3.3 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 and Tutan, 2015). Content freshness refers to the reverse difference of one post to its previous post (Li, et al., 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 and 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 and 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 analysed using sentiment 140 package in R. Using this algorithm, each comment was classified as positive, negative, or neutral.

5. Analysis

5.1. Validity checks

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

5.1.1. 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.

--Insert Table 3 about here--

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 (H_0) assumes that the true mean difference (μ_d) is equal to zero.

--Insert Table 4 about here--

5.1.2. 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 and Van Aelst, 2018). Correlation in error terms between equations with different dependent variables is particularly likely when both equations utilize the same dataset (Engle and 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.

--Insert Table 5 about here--

As can be seen in Table 5, the correlation between the No. of likes and No. 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.

--Insert Table 6 about here--

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

--Insert Table 7 about here--

Cross-equation test across different independent variables is the test for the equality of coefficients- for similar independent variables- 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.

5.1.3. 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 of 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 modelling (see Benitez, Henseler and Roldán, 2016). The path models are depicted in Figure 2. The regression result of the path analysis for both dependent variables is shown in Table 8.

--Insert Table 8 about here--

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.

5.2 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 subcategories content (within each of the three overarching content types) that it can change from zero to four. 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 and 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 poisson distribution, net sentiment followed the normal distribution with high kurtosis. One of the assumptions of the linear regression is multivariate normality (Uyanik and 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 and 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:

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

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 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 nonsignificant, 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 et al., 2010).

6. 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 and 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 and 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 and 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 support H5b, 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.

7. Discussion and Implications

Today's business environment has become more interactive, where customers are continuously engaged with offerings and activities of firms (Dolan et al, 2019). Customers engage for various reasons through various objects, such as product or service offerings (Brodie et al., 2011), media (Calder, Malthouse and Schaedel, 2009), activities, and events (Vivek et al. 2012). Although recent research has explored both the antecedents and consequences of customer engagement (Gambetti, Graffigna and Biraghi, 2012; Leckie, Nyadzayo and 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 et al., 2019). While much of the literature identifies individual-related factors as antecedents of customer engagement, few studies (e.g., Cvijikj and Michahelles, 2013; Lee, Hosanagar and Nair, 2018, Dolan, et al., 2019) 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 et al., 2019) have focussed 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.

8. 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 data set 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 versus 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, for example on video production and placement, may lead to higher impressions, and thus higher engagement. Further, a more complex data set 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 data set 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 data set 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 (Aboulhossn, 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 (Aboulhossn, 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 towards 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.

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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 et al., 2019)	Empirical	Informational content provides users with resourceful and helpful information.	Significant effect	Likes, shares, comments	Facebook
(Coelho, Oliveira and Almeida, 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, Spiller and Hettche, 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 Michahells, 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, Gensler and Leeflang, 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 et al., 2019)	Empirical	Entertaining content refers to the extent that is fun and entertaining to media users.	Significant positive effect of entertaining content on likes	Likes, shares, comments	Facebook
		Relational content refers to the extent that meets the consumer's need for integration and social interaction and desire for social benefits.			
(Coelho, Oliveira and Almeida, 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	Significant effect for likes on Instagram Non-significant effect for the rest		

		sphere and posts with entertaining content, to attract the attention of their followers and acquire larger numbers of likes and comments			
(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, Milne and Brown, 2013)	Empirical	Advertising the name of the firm	Significant negative effect	Likes	Facebook
		Motivating individuals to express their feeling by engaging with the message	Significant positive effect		
(De Vries, Gensler and Leeftang, 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
(Ashley and Tuten, 2015)	Conceptual	How they will experience sight, sound, taste, touch, smells.	-	-	Twitter, Facebook, MySpace, forums, and blogs
(Cvijikj and Michahells, 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, Spiller and Hettche, 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 et al., 2019)	Empirical	Remunerative content provides monetary or incentive rewards.	Significant positive effect on likes and shares	Likes, share and comments	Facebook
(Coelho, Oliveira and Almeida, 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, Spiller and Hettche, 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, Milne and Brown, 2013)	Empirical	Content encouraging an immediate sale	Non-significant negative effect	Likes	Facebook
(Cvijikj and Michahelle, 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

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	.763	0.769	0.605	0.621
	F	196.808***	141.019***	93.937***	70.071***
	(Constant)	1.731	1.720	-.498	-0.532
Independent variables	Format	.258***	0.306***	-.566***	-0.628***
	Platform	.250***	0.216***	-.405***	-0.378***
	Rational	-.239***	-0.241**	.260***	0.254***
	Emotional	-.005	0.003	-.069*	-0.085*
	Transactional	-.082*	-0.116**	.165***	0.163**
Control variables	Content freshness	-.018	-0.024	-.229~	-0.180
	Company	-.408***	-0.406***	.247***	0.265***
	Scheduling	-.050*	-0.044~	.071*	0.065~
	Time lag effect	Like lag	.209***	0.202***	-
		Comment lag	-	-	.090**
	Net sentiment	.967***	0.832***	-.789***	-0.737**
	Engagement effect	No. of likes	-	-	.733***
		No. of comments	.374***	0.393***	-
Interactions	Rational _format	.105**	0.123**	-.123**	-0.119*
	Rational _platform	.112***	0.109**	-.130**	-0.133*
	Emotional _format	-.055*	-0.069*	.132***	0.146***
	Emotional _platform	.029	0.034	-.004	-0.009
	Transactional _format	.021	0.020	.073	0.092
	Transactional _platform	.069*	0.106*	-.258***	-0.310***

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

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	.01437	.26673	.01498	-.01510	.04385	.959	316	.338
Pair 2	Estimated comment – Real comment	.00781	.38088	.02139	-.03428	.04990	.365	316	.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	.125**
Norm likes	.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	-.499**
Standardized residual comment	-.499**	1

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

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

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			-.498			
Independent Variables	Format	.258***	0.209	** 0.001	-.566***	-0.414	***0.000	
	Platform	.250***	0.235	*** 0.000	-.405***	-0.344	*** 0.000	
	Rational	-.239***	-0.305	*** 0.000	.260***	0.290	*** 0.000	
	Emotional	-.005	-0.011	0.829	-.069*	-0.109	* 0.017	
	Transactional	-.082*	-0.080	~ 0.089	.165***	0.144	** 0.001	
Controls	Freshness	-.018	-0.003	0.643	-.229~	-0.034	* 0.025	
	Company	-.408***	-0.387	*** 0.000	.247***	0.213	*** 0.000	
	Scheduling	-.050*	-0.043	** 0.001	.071*	0.055	** 0.008	
	Time lag	Like lag	.209***	0.205	*** 0.000	-	-	-
		Comment lag	-	-	-	.090**	0.092	*** 0.000
	Engagem ent effect	No of Likes	-	-	-	.733***	0.658	*** 0.000
		No of Comments	.374***	0.416	*** 0.000	-	-	-
	Net sentiment	.967***	0.126	*** 0.000	-.789***	-0.092	*** 0.000	
Interactions	Rational _format	.105**	0.101	* 0.010	-.123**	-0.102	* 0.014	
	Rational _platform	.112***	0.087	** 0.001	-.130**	-0.089	** 0.007	
	Emotional _format	-.055*	-0.102	~ 0.070	.132***	0.223	*** 0.000	
	Emotional _platform	.029	0.058	0.196	-.004	-0.005	0.920	
	Transactional _format	.021	0.024	0.647	.073	0.082	0.152	
	Transactional _platform	.069*	0.091	~ 0.068	-.258***	-0.301	*** 0.000	

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	.763	.572	.605
	F	285.099***	196.808***	126.301***	93.937***
	(Constant)	1.593	1.731	-.369	-.498
Independent Variables	Format	.263***	.258***	-.390***	-.566***
	Platform	.399***	.250***	-.712***	-.405***
	Rational	-.131***	-.239***	.146***	.260***
	Emotional	-.025*	-.005	.017	-.069*
	Transactional	-.020	-.082*	.071	.165***
Controls	Freshness	.022	-.018	-.319	-.229~
	Company	-.440***	-.408***	.281***	.247***
	Scheduling	-.051*	-.050*	.073	.071*
	Time lag	Like Lag	.235***	.209***	-
		Comment Lag	-	-	.113***
	Net Sentiment		.999***	.967***	-.814***
	Engage ment effect	No of Likes	-	-	.692***
		No of Comments	.352***	.374***	-
Interactions	Rational _format	-	.105**	-	-.123**
	Rational _platform	-	.112***	-	-.130**
	Emotional _format	-	-.055*	-	.132***
	Emotional _platform	-	.029	-	-.004
	Transactional _format	-	.021	-	.073
	Transactional _platform	-	.069*	-	-.258***

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

Figure 1: Research conceptual framework

Figure 2. Path models for Endogeneity Check

Appendices

Appendix 1- Normality tests of the residuals of the dependent variables

Descriptives				
			Statistic	Std. Error
Standardized Residual	Mean		.0000000	.03084157
	95% Confidence Interval for Mean	Lower Bound	-.0605193	
		Upper Bound	.0605193	
	5% Trimmed Mean		.0044642	
	Median		.0395162	
	Variance		.984	
	Std. Deviation		.99173740	
	Minimum		-3.58293	
	Maximum		4.97643	
	Range		8.55936	
	Interquartile Range		1.18499	
	Skewness		-.023	.076
	Kurtosis		1.861	.152
Standardized Residual	Mean		.0000000	.03084157
	95% Confidence Interval for Mean	Lower Bound	-.0605193	
		Upper Bound	.0605193	
	5% Trimmed Mean		-.0240828	
	Median		-.0695507	
	Variance		.984	
	Std. Deviation		.99173740	
	Minimum		-2.89593	
	Maximum		5.27864	
	Range		8.17457	
	Interquartile Range		1.23213	
	Skewness		.583	.076
	Kurtosis		1.999	.152

Tests of Normality						
	Kolmogorov-Smirnov ^a			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Standardized Residual	.046	1034	.000	.978	1034	.000
Standardized Residual	.034	1034	.008	.978	1034	.000

a. Lilliefors Significance Correction

Appendix 2- Breusch-pagon test result

Seemingly unrelated regression

Equation	Obs	Parms	RMSE	"R-sq"	chi2	P
norm_comment	1,034	17	.3892642	0.5663	2369.15	0.0000
norm_likes	1,034	17	.2714129	0.7379	4148.94	0.0000

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
norm_comment						
format	-.6112236	.0915875	-6.67	0.000	-.7907319	-.4317154
platform	-.4965942	.0802004	-6.19	0.000	-.6537841	-.3394044
rational	.3604495	.0395838	9.11	0.000	.2828666	.4380324
emotional	-.0597401	.0313149	-1.91	0.056	-.1211162	.0016361
transactional	.1818551	.0467694	3.89	0.000	.0901887	.2735214
freshness	-.1645715	.1350746	-1.22	0.223	-.4293128	.1001698
company	.4922375	.0367898	13.38	0.000	.4201308	.5643442
scheduling	.0877933	.028606	3.07	0.002	.0317266	.14386
commenlag	.0269721	.0227977	1.18	0.237	-.0177106	.0716547
norm_likes	1.130226	.0331667	34.08	0.000	1.06522	1.195231
norm_net_sentiment	-1.227625	.194635	-6.31	0.000	-1.609103	-.8461477
rational_format	-.1704163	.0459007	-3.71	0.000	-.26038	-.0804525
rational_plat	-.1710589	.0449596	-3.80	0.000	-.2591781	-.0829396
emotional_format	.1447898	.0348184	4.16	0.000	.076547	.2130326
emotional_plat	-.022199	.0304095	-0.73	0.465	-.0818004	.0374025
transactional_format	.0523506	.0527908	0.99	0.321	-.0511175	.1558187
transactional_plat	-.2613762	.0480432	-5.44	0.000	-.3555391	-.1672134
_cons	-1.605886	.1356861	-11.84	0.000	-1.871826	-1.339946
norm_likes						
format	.368652	.0641159	5.75	0.000	.2429872	.4943169
platform	.3287968	.0553335	5.94	0.000	.220345	.4372485
rational	-.2729714	.0269034	-10.15	0.000	-.325701	-.2202418
emotional	.0175725	.0218272	0.81	0.421	-.0252081	.060353
transactional	-.1123408	.0325352	-3.45	0.001	-.1761085	-.0485731
freshness	.0499945	.0935515	0.53	0.593	-.1333631	.2333521
company	-.4207702	.0259277	-16.23	0.000	-.4715876	-.3699529
scheduling	-.0614589	.0198317	-3.10	0.002	-.1003283	-.0225895
likelag	.1217981	.0212439	5.73	0.000	.0801609	.1634353
norm_comment	.5727944	.0163507	35.03	0.000	.5407475	.6048413
norm_net_sentiment	1.020041	.1330723	7.67	0.000	.7592245	1.280858
rational_format	.1246346	.0317675	3.92	0.000	.0623716	.1868977
rational_plat	.1286424	.0311107	4.13	0.000	.0676666	.1896181
emotional_format	-.0837326	.0242919	-3.45	0.001	-.1313439	-.0361213
emotional_plat	.0258208	.0210959	1.22	0.221	-.0155264	.0671679
transactional_format	-.0056855	.0366683	-0.15	0.877	-.0775827	.0662118
transactional_plat	.1332132	.0337609	3.95	0.000	.0670431	.1993833
_cons	1.611407	.0911922	17.67	0.000	1.432674	1.790141

Correlation matrix of residuals:

	norm_comment	norm_likes
norm_comment	1.0000	
norm_likes	-0.4986	1.0000

Breusch-Pagan test of independence: chi2(1) = 257.008, Pr = 0.0000

Appendix 3

Emotional

Seemingly unrelated regression

Equation	Obs	Parms	RMSE	"R-sq"	chi2	P
norm_comment	1,034	17	.3896171	0.5656	2358.69	0.0000
norm_likes	1,034	17	.2713865	0.7380	4139.76	0.0000

(1) [norm_comment]emotional - [norm_likes]emotional = 0

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
norm_comment						
format	-.5391987	.0809369	-6.66	0.000	-.6978321	-.3805652
platform	-.4686837	.0785326	-5.97	0.000	-.6226048	-.3147625
rational	.3950142	.0336382	11.74	0.000	.3290846	.4609439
emotional	-.0120157	.0128736	-0.93	0.351	-.0372475	.0132162
transactional	.1860678	.0467228	3.98	0.000	.0944928	.2776429
freshness	-.1674771	.1351353	-1.24	0.215	-.4323374	.0973833
company	.4947095	.036762	13.46	0.000	.4226574	.5667616
scheduling	.0895976	.0285986	3.13	0.002	.0335454	.1456498
commenlag	.0266479	.0228321	1.17	0.243	-.0181022	.0713979
norm_likes	1.12976	.0332084	34.02	0.000	1.064673	1.194847
norm_net_sentiment	-1.231967	.1947057	-6.33	0.000	-1.613583	-.8503505
rational_format	-.1982738	.0427523	-4.64	0.000	-.2820668	-.1144809
rational_plat	-.1830117	.0443954	-4.12	0.000	-.2700251	-.0959982
emotional_format	.1066435	.0263531	4.05	0.000	.0549924	.1582946
emotional_plat	-.0383522	.0288355	-1.33	0.184	-.0948688	.0181644
transactional_format	.0490614	.0527788	0.93	0.353	-.0543832	.1525059
transactional_plat	-.2629618	.0480577	-5.47	0.000	-.3571533	-.1687704
_cons	-1.693471	.1241761	-13.64	0.000	-1.936852	-1.45009
norm_likes						
format	.3234327	.0582913	5.55	0.000	.2091838	.4376816
platform	.3108925	.0543724	5.72	0.000	.2043246	.4174604
rational	-.2939137	.0238122	-12.34	0.000	-.3405848	-.2472427
emotional	-.0120157	.0128736	-0.93	0.351	-.0372475	.0132162
transactional	-.1146749	.0325374	-3.52	0.000	-.178447	-.0509028
freshness	.0514117	.0936464	0.55	0.583	-.1321318	.2349552
company	-.4217483	.0259558	-16.25	0.000	-.4726207	-.3708758
scheduling	-.0624754	.0198427	-3.15	0.002	-.1013664	-.0235844
likelag	.1233517	.021277	5.80	0.000	.0816496	.1650538
norm_comment	.5714085	.0163751	34.90	0.000	.539314	.6035031
norm_net_sentiment	1.022126	.1332057	7.67	0.000	.7610473	1.283204
rational_format	.1415631	.0301347	4.70	0.000	.0825002	.200626
rational_plat	.135877	.030838	4.41	0.000	.0754356	.1963185
emotional_format	-.0599944	.0197797	-3.03	0.002	-.098762	-.0212269
emotional_plat	.0357698	.0202634	1.77	0.078	-.0039457	.0754852
transactional_format	-.003418	.0366981	-0.09	0.926	-.0753449	.068509
transactional_plat	.1335944	.0337956	3.95	0.000	.0673562	.1998327
_cons	1.664525	.0855985	19.45	0.000	1.496755	1.832295

Emotional_platform

Seemingly unrelated regression

Equation	Obs	Parms	RMSE	"R-sq"	chi2	P
norm_comment	1,034	17	.3892694	0.5663	2369.27	0.0000
norm_likes	1,034	17	.2715331	0.7377	4145.03	0.0000

(1) [norm_comment]emotional_plat - [norm_likes]emotional_plat = 0

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
norm_comment						
format	-.5983419	.0908106	-6.59	0.000	-.7763275	-.4203564
platform	-.5493018	.0633079	-8.68	0.000	-.673383	-.4252205
rational	.352232	.0388488	9.07	0.000	.2760897	.4283744
emotional	-.0704574	.0296794	-2.37	0.018	-.1286281	-.0122868
transactional	.1814182	.0467744	3.88	0.000	.0897421	.2730943
freshness	-.1517932	.1345631	-1.13	0.259	-.4155322	.1119457
company	.4906652	.0367717	13.34	0.000	.418594	.5627364
scheduling	.0874954	.0286088	3.06	0.002	.0314231	.1435676
commenlag	.0269981	.0228035	1.18	0.236	-.0176961	.0716922
norm_likes	1.128639	.0331499	34.05	0.000	1.063667	1.193612
norm_net_sentiment	-1.228217	.1946621	-6.31	0.000	-1.609748	-.8466864
rational_format	-.1721499	.045878	-3.75	0.000	-.2620691	-.0822307
rational_plat	-.1544386	.0422109	-3.66	0.000	-.2371704	-.0717068
emotional_format	.1377	.0341897	4.03	0.000	.0706895	.2047105
emotional_plat	.0075467	.0124174	0.61	0.543	-.016791	.0318845
transactional_format	.050703	.0527757	0.96	0.337	-.0527354	.1541414
transactional_plat	-.2592669	.0480097	-5.40	0.000	-.3533642	-.1651696
_cons	-1.582047	.1339673	-11.81	0.000	-1.844618	-1.319476
norm_likes						
format	.3609224	.0637294	5.66	0.000	.236015	.4858298
platform	.361433	.0461999	7.82	0.000	.2708828	.4519831
rational	-.2681283	.0265297	-10.11	0.000	-.3201255	-.216131
emotional	.0241426	.0209531	1.15	0.249	-.0169248	.0652099
transactional	-.1121321	.0325443	-3.45	0.001	-.1759177	-.0483466
freshness	.0421764	.0932942	0.45	0.651	-.1406769	.2250297
company	-.4200651	.0259284	-16.20	0.000	-.4708837	-.3692464
scheduling	-.0613217	.0198372	-3.09	0.002	-.1002018	-.0224415
likelag	.1221986	.0212497	5.75	0.000	.08055	.1638472
norm_comment	.573121	.016354	35.04	0.000	.5410678	.6051742
norm_net_sentiment	1.021267	.1331067	7.67	0.000	.7603824	1.282151
rational_format	.125788	.0317585	3.96	0.000	.0635425	.1880335
rational_plat	.1185261	.0296524	4.00	0.000	.0604084	.1766438
emotional_format	-.0794012	.0239611	-3.31	0.001	-.1263642	-.0324383
emotional_plat	.0075467	.0124174	0.61	0.543	-.016791	.0318845
transactional_format	-.004639	.0366809	-0.13	0.899	-.0765323	.0672543
transactional_plat	.1319442	.0337505	3.91	0.000	.0657944	.1980941
_cons	1.597892	.0903537	17.68	0.000	1.420802	1.774982

Transactional_Format

Seemingly unrelated regression

Equation	Obs	Parms	RMSE	"R-sq"	chi2	P
norm_comment	1,034	17	.3893659	0.5661	2366.96	0.0000
norm_likes	1,034	17	.2713769	0.7380	4147.66	0.0000

(1) [norm_comment]transactional_format - [norm_likes]transactional_format = 0

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
norm_comment						
format	-.5734343	.0763401	-7.51	0.000	-.7230582	-.4238104
platform	-.5036408	.079636	-6.32	0.000	-.6597245	-.3475572
rational	.3634914	.039363	9.23	0.000	.2863414	.4406414
emotional	-.0588576	.0312957	-1.88	0.060	-.1201961	.0024809
transactional	.203467	.0366894	5.55	0.000	.131557	.2753769
freshness	-.1643157	.1350905	-1.22	0.224	-.4290882	.1004569
company	.4907462	.0367611	13.35	0.000	.4186959	.5627966
scheduling	.0882165	.0286033	3.08	0.002	.032155	.1442779
comenlag	.0270714	.0228076	1.19	0.235	-.0176307	.0717734
norm_likes	1.130486	.0331665	34.09	0.000	1.065481	1.195491
norm_net_sentiment	-1.221351	.194505	-6.28	0.000	-1.602574	-.8401282
rational_format	-.1720412	.0458512	-3.75	0.000	-.2619079	-.0821744
rational_plat	-.1743178	.0447463	-3.90	0.000	-.2620189	-.0866168
emotional_format	.1434849	.0347795	4.13	0.000	.0753184	.2116514
emotional_plat	-.021516	.0304001	-0.71	0.479	-.0810991	.0380672
transactional_format	.0164534	.0215901	0.76	0.446	-.0258624	.0587693
transactional_plat	-.252706	.0466213	-5.42	0.000	-.3440822	-.1613299
_cons	-1.630854	.131097	-12.44	0.000	-1.887799	-1.373909
norm_likes						
format	.3450981	.0558766	6.18	0.000	.235582	.4546141
platform	.3329309	.0550604	6.05	0.000	.2250144	.4408473
rational	-.2747338	.0268027	-10.25	0.000	-.3272661	-.2222016
emotional	.016972	.0218188	0.78	0.437	-.025792	.059736
transactional	-.1255422	.0272821	-4.60	0.000	-.1790141	-.0720703
freshness	.0497529	.0935745	0.53	0.595	-.1336497	.2331556
company	-.419692	.0258994	-16.20	0.000	-.4704539	-.3689302
scheduling	-.0616886	.019834	-3.11	0.002	-.1005626	-.0228146
likelag	.122036	.0212548	5.74	0.000	.0803773	.1636947
norm_comment	.5722813	.0163518	35.00	0.000	.5402323	.6043304
norm_net_sentiment	1.015902	.1329926	7.64	0.000	.755241	1.276563
rational_format	.1255753	.0317494	3.96	0.000	.0633477	.1878029
rational_plat	.130599	.0310061	4.21	0.000	.0698281	.1913699
emotional_format	-.0828464	.0242705	-3.41	0.001	-.1304158	-.035277
emotional_plat	.0254024	.0210936	1.20	0.228	-.0159402	.0667451
transactional_format	.0164534	.0215901	0.76	0.446	-.0258624	.0587693
transactional_plat	.1277137	.0329696	3.87	0.000	.0630944	.192333
_cons	1.626437	.0889615	18.28	0.000	1.452076	1.800798

Appendix 4

		Number of Likes				Number of Comments			
		Original	Emotional Fix	Emotional _plat	Transactional _format	With Interaction original	Emotional Fix	Emotional _plat Fix	Transactional _format Fix
	R Square	0.7671	0.7380	0.7377	0.7380	0.6112	0.5656	0.5663	0.5661
	F	196.808***				93.937***			
	(Constant)	1.731	1.664	1.598	1.626	-.498	-1.693	-1.582	-1.631
Independent Variables	Format	.258** *	0.323***	0.361**	0.345***	-.566**	-.539**	-.598** *	-0.573***
	Platform	.250** *	0.311***	0.361**	0.333***	-.405**	-.468**	-.549** *	-0.504***
	Rational	-.239** *	-.0294***	-.0268**	-0.275***	.260**	.395**	0.352** *	0.363***
	Emotional	-.005	0.012	0.024	0.017	-.069*	-.0120	-0.070*	-0.059~
	Transactional	-.082*	0.115***	0.112* *	-0.126***	.165**	.186**	0.181** *	0.203
Controls	Freshness	-.018	0.051	0.042	0.050	-.229~	-.167	-0.152	-0.164
	Company	-.408** *	0.422***	0.420**	-0.420***	.247**	.494**	0.491** *	0.491***
	Scheduling	-.050*	0.062**	0.061* *	-0.062**	.071*	.089* *	0.087**	0.088**
	Like Lag	.209** *	0.123***	0.122**	0.122***	-	-	-	
	Comment Lag	-	-	-		.090* *	.026	.027	.027
	No of Likes	-	-	-		.733**	1.12***	1.129** *	1.130***
	No of Comments	.374** *	0.571***	0.573**	0.572***	-	-		

	Net Sentiment of the comments	.967** *	1.02 2***	1.021* **	1.016***	-.789* **	-.123***	-.1228** *	-1.221***
Interactions	Rational _format	.105* *	0.14 2***	0.126* **	0.126***	-.123* *	-.19 8***	-.0172** *	-0.172***
	Rational _platform	.112* **	0.13 6***	0.119* **	0.131***	-.130* *	-.18 3***	-.0154** *	-0.174***
	Emotional _format	-.055* *	-.06 0**	-.079* *	-0.083**	.132* **	.10 6***	.0138** *	0.143***
	Emotional _platform	.029	0.03 6~	0.008	0.025	-.004	.03 8	0.008	-0.022
	Transactional _format	.021	0.03 7	-.004	.016	.073	.04 9	0.053	.016
	Transactional _platform	.069* *	0.13 4***	0.132* **	0.128***	-.258* **	-.26 2***	-.0259** *	-0.253***

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

Appendix 5

	Norm. Likert		Norm. Composite		Norm. Net-Advantage		Rational format		Rational split		Emotional format		Emotional split		Transrational format		Transrational split		Standardized Residual	Standardized Residual
Norm. Likert	Pearson Correlation	1	.125"	-.057"	.466"	.466"	.139"	.148"	.199"	.138"	.215"	.099"	.483"	.000						
	Sig. (2-tailed)		.000	.006	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	1.000
Norm. Composite	Pearson Correlation	1038	1038	1034	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1034	1034
	Sig. (2-tailed)	.125"	1	.496"	-.131"	-.131"	.047"	.047"	.047"	.047"	.047"	.047"	.047"	.047"	.047"	.047"	.047"	.047"	.047"	.047"
Norm. Composite	Pearson Correlation	.000	.000	.000	.000	.000	.132	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	Sig. (2-tailed)	N	1038	1038	1034	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1034	1034
Composite	Pearson Correlation	-.057	.496"	1	.167"	.167"	.111"	.159"	-.266"	-.493"	-.296"	-.551"	-.296"	-.551"	-.296"	-.551"	-.296"	-.551"	-.070"	.000
	Sig. (2-tailed)	.066	.000		.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.025	1.000
Norm. Net-Advantage	Pearson Correlation	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034
	Sig. (2-tailed)	.466"	-.131"	-.167"	-.167"	1	.990	.040	.040	.040	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
Rational format	Pearson Correlation	1038	1038	1034	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1034	1034
	Sig. (2-tailed)	.139"	.000	.047"	.111"	.000	.990	.040	.040	.040	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
Rational format	Pearson Correlation	.000	.132	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	Sig. (2-tailed)	N	1038	1038	1034	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1034	1034
Rational split	Pearson Correlation	.148"	-.167"	-.159"	.064"	.064"	.482"	.482"	1	-.148"	.081	-.020	.233"	.000						.000
	Sig. (2-tailed)	.000	.000	.000	.040	.040	.000	.000	.000	.050	.521	.000	.000	.000	.000	.000	.000	.000	.000	1.000
Emotional format	Pearson Correlation	1038	1038	1034	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1034	1034
	Sig. (2-tailed)	.199"	-.267"	-.258"	.228"	.228"	-.095"	-.148"	1	.566"	.500"	.290"	.290"	.000	.000	.000	.000	.000	.000	.000
Emotional split	Pearson Correlation	.000	.000	.000	.000	.000	.002	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	Sig. (2-tailed)	N	1038	1038	1034	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1034	1034
Emotional split	Pearson Correlation	.138"	-.465"	-.483"	.192"	.192"	-.229"	.061	.566"	1	.309"	.675"	.675"	.000	.000	.000	.000	.000	.000	.000
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.050	.050	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
Transrational format	Pearson Correlation	1038	1038	1034	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1034	1034
	Sig. (2-tailed)	.215"	-.296"	-.296"	.240"	.240"	.158"	-.020	.500"	.309"	1	.572"	.572"	.000	.000	.000	.000	.000	.000	.000
Transrational split	Pearson Correlation	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	Sig. (2-tailed)	N	1038	1038	1034	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1038	1034	1034
Transrational split	Pearson Correlation	.099"	-.542"	-.551"	.189"	.189"	.233"	.233"	.280"	.675"	.675"	.675"	.675"	.000	.000	.000	.000	.000	.000	.000
	Sig. (2-tailed)	.004	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
Standardized Residual	Pearson Correlation	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	Sig. (2-tailed)	N	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034
Standardized Residual	Pearson Correlation	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	Sig. (2-tailed)	N	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034
Standardized Residual	Pearson Correlation	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	Sig. (2-tailed)	N	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034	1034

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

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