Unpacking the impact of social media analytics on customer satisfaction: Do external stakeholder characteristics matter?

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Abstract

Purpose: Underpinned by the lens of Contingency Theory (CT), the purpose of this paper is to empirically evaluate whether the impact of social media analytics (SMA) on customer satisfaction (CS) is contingent on the characteristics of different external stakeholders, including business partners (i.e. partner diversity), competitors (i.e. localised competition) and customers (i.e. customer engagement).

Design/Methodology/Approach: Using both subjective and objective measures from multiple sources, we collected primary data from 141 hotels operating in Greece and their archival data from TripAdvisor and the Hellenic Chamber of Hotels (HCH) database to test the hypothesised relationships. Data were analysed through structural equation modelling.

Findings: This study confirms the positive association between SMA and CS, but it remains subject to the varied characteristics of external stakeholders. We find that an increase in CS due to the implementation of SMA is more pronounced for firms that (1) adopt a selective distribution strategy where a limited number of business partners are chosen for collaboration or (2) operate in a highly competitive local environment. The results further indicate the high level of customer engagement amplify moderating effect of partner diversity (when it is low) and localised competition (when it is high) on the SMA–CS relationship.

Originality/Value: The study provides novel insights for managers on the need to consider external stakeholder characteristics when implementing SMA to enhance firms' CS, and for researchers on the value of studying SMA implementation from the CT perspective.

Keywords: Social media analytics, Contingency theory, Service operations, Customer satisfaction

Article Classification: Research paper

1. Introduction

Operations and supply chain management (OSCM) scholars have recognised that firms are increasingly utilising social media analytics (SMA) to garner market reactions from their external constituents in order to satisfy customers' various demands (Gu and Ye, 2014; Chan *et al.*, 2016; Lam *et al.*, 2016; Cui *et al.*, 2018). For instance, through using multi-channel SMA, the Intercontinental Hotels Group (IHG) generated the corporate metrics and a scorecard with over 5,000 variables from social media traffic data, and to link those to deliver brand preference and customer engagement (Gibb, 2015). However, without appropriate governance of SMA, firms may fail to address customer concerns due to slow response to unexpected consequences. For example, United Airlines failed to respond adequately or in a timely manner to harsh comments regarding the dragging incident, posted on online social media platforms. As a result, United Airlines lost 800 million USD in market value within one day, and was eventually forced to introduce costly policies to avoid further reputational loss and a decrease in bookings (Tse *et al.*, 2018).

These examples of success and failure in using SMA show that it could play a pivotal role in achieving customer satisfaction (CS) in today's highly dynamic business environment. Although the importance of SMA has been widely demonstrated in the OSCM literature (e.g. Abrahams *et al.*, 2015; Chan *et al.*, 2016), empirical evidence as to the impact of SMA on CS is scarce. Some practitioners question the benefits of using SMA. Anecdotal evidence reported by *New York* magazine indicates that social media traffic metrics are fabricated and thus business insights generated from social media data are questionable (Read, 2018). Whether SMA can improve CS more generally remains an open question. This question is particularly important for hospitality sector because hospitality practitioners are heavily reliant on social media platforms as a means of capturing user-generated content for customer analytics and customer relationship management (Ghose *et al.*, 2012; Proserpio and Zervas, 2017).

SMA has been viewed as a technical solution or an organisation and process issue (Fan and Gordon, 2014). The majority of the existing studies on the topic have examined the effect of analytics-related resources and capabilities on organisational performance and the moderating role of intra-organisational issues, such as organisational changes in business processes, business strategies and organisational routines (Srinivasan and Swink, 2018). For instance, Hazen et al. (2014) emphasise the need for the monitoring and control of data quality in big data analytics (BDA) initiatives, while Ross *et al.* (2013) suggest that an organisational culture of evidence-based decision making enables firms to ensure the decision-making quality, thereby improving overall firm performance. Apart from the identification of these internal conditions, a discussion regarding how the role of external stakeholders can catalyse the conversion of SMA investments to business value is noticeably absent from the extant literature.

In fact, the value of analytics to a firm is, to a large extent, determined by its external stakeholders, such as business partners, competitors and customers (Grover *et al.*, 2018; Park *et al.*, 2017). In information systems (IS) literature, Melville *et al.* (2004) recognise that external stakeholders (e.g. trading partners and customers) and the competitive environment play crucial roles in driving business value through information technology (IT) capabilities, while Grover *et al.* (2018) suggest that integrating the views of external stakeholders is a key priority when implementing BDA. It is acknowledged that firms are required to carefully monitor their external environments and stakeholders when developing their analytics capability (Chen *et al.*, 2015; Müller *et al.*, 2018).

Furthermore, the important role of customer engagement in OSCM has been widely recognised by scholars across a range of contexts, from the manufacturing sector (e.g. Gosling *et al.*, 2017) to the service sector (e.g. Brandon-Jones *et al.*, 2016). While several studies have recognised that a successful BDA implementation heavily depends on assimilating and transforming customer knowledge into the firm's knowledge base (Cohen, 2018; Grover *et al.*, 2018), very little attention has been paid to explaining how a firm should make appropriate responses to the external environment that is characterised by their customer engagement level when initiating SMA. Following the logic of these thoughts, three characteristics of external stakeholders (i.e., *partner diversity*, *customer engagement*, and *localised competition*) are proposed for examination as possible moderators of the relationship between SMA and CS through the lens of contingency theory (CT). This examination could readdress a classical organisation theory question raised by McArthur and Nystrom (1991) "*Do environmental conditions interact with strategies as joint determinants of company performance?*" (P. 349) in general, and specifically, provide hospitality practitioners with more specific implications of how the characteristics of external stakeholder can catalyse the conversion of SMA investments to business value.

Our study makes several important contributions to the OSCM literature. ***First***, hospitality organisations are more likely to improve CS when their SMA initiatives are properly implemented. This is among the first research to provide empirical evidence on the positive impact of SMA on CS in the hospitality context. ***Second***, our study reveals the moderating role of external stakeholder characteristics in the SMA–CS relationship. We offer a complementary explanation as to whether the diversity of business partner and the level of customer engagement are beneficial for hotels that deploy SMA to enhance CS. Our theoretical perspective helps to reaffirm a theoretical view proposed by Melville *et al.* (2004), who contend that external stakeholders (e.g., trading partners) play a crucial role in the IT business value generation of the focal firm when IT spans firm boundaries. ***Third***, underpinned by contingency theory, our finding confirms that the SMA–CS relationship would be strengthened for firms that operate in a highly localised competition market. In view of our suggestion that businesses must develop SMA in accordance with their external stakeholders in order to improve their CS, this paper extends the research that interprets the implementation of analytics as strategic change within an organisation.

2. Theoretical Background

2.1. Review on the link between analytics-related resources and capability and *organisational performance*

Recent studies have sought to understand under what internal and external conditions an organisation can enhance organisational performance through the deployment of analytics resources and capabilities. One strand of this research has tended to investigate how internal environment (the organisation itself) conditions moderate the relationship between analytics-related resources and capability and organisational performance. Internal environment conditions such as organisational flexibility (Dubey *et al.*, 2019; Srinivasan and Swink, 2018), organisational size (Park *et al.*, 2017), strategic alignment (Akter *et al.*, 2016), and task-technology fit (Ghasemaghaei *et al.*, 2017) have been considered as complementary to analytics capability. For instance, Srinivasan and Swink (2018) claim that in firms with high levels of organisational flexibility, analytics capability will have a more powerful effect on operating performance. Hallikainen *et al.* (2020) conduct an empirical investigation of 417 B2B firms to examine the mechanisms by which customer analytics indirectly influence sales growth and customer relationship performance. Their findings show that customer analytics significantly fosters sales growth, and this effect would be stronger for firms that have a high level of analytics culture.

Another strand of the recent research indicates that the role of external stakeholder characteristics are also important context factors that could amplify or lessen the impact of analytics resources and capability on firm performance. Chen *et al.* (2015) claim that the effectiveness of BDA is more pronounced in highly dynamic industrial environments, where it enables firms to better use big data resources to improve asset productivity and business growth. Using a longitudinal dataset that includes information about analytics assets owned by 814 companies from 2008 to 2014, Müller *et al.* (2018) conclude that firms operating in IT-intensive or highly competitive industries are most likely to create business value from their BDA assets.

Figure 1 below provides an overview of bodies of knowledge and the central works that identify the moderating role in the analytics-related resources and capability–organisational performance relationship. Although prior research has explored various internal environment conditions as complementary to analytics resources and capability for improving firm performance, surprisingly, no study has investigated the possibility that SMA contributes to CS considering the distinctive roles of external stakeholders such as business partners and customers. Our study complements the existing OSCM literature theoretically by hypothesising and empirically testing the moderating role of external stakeholder characteristics in the SMA–CS relationship in the hospitality sector.

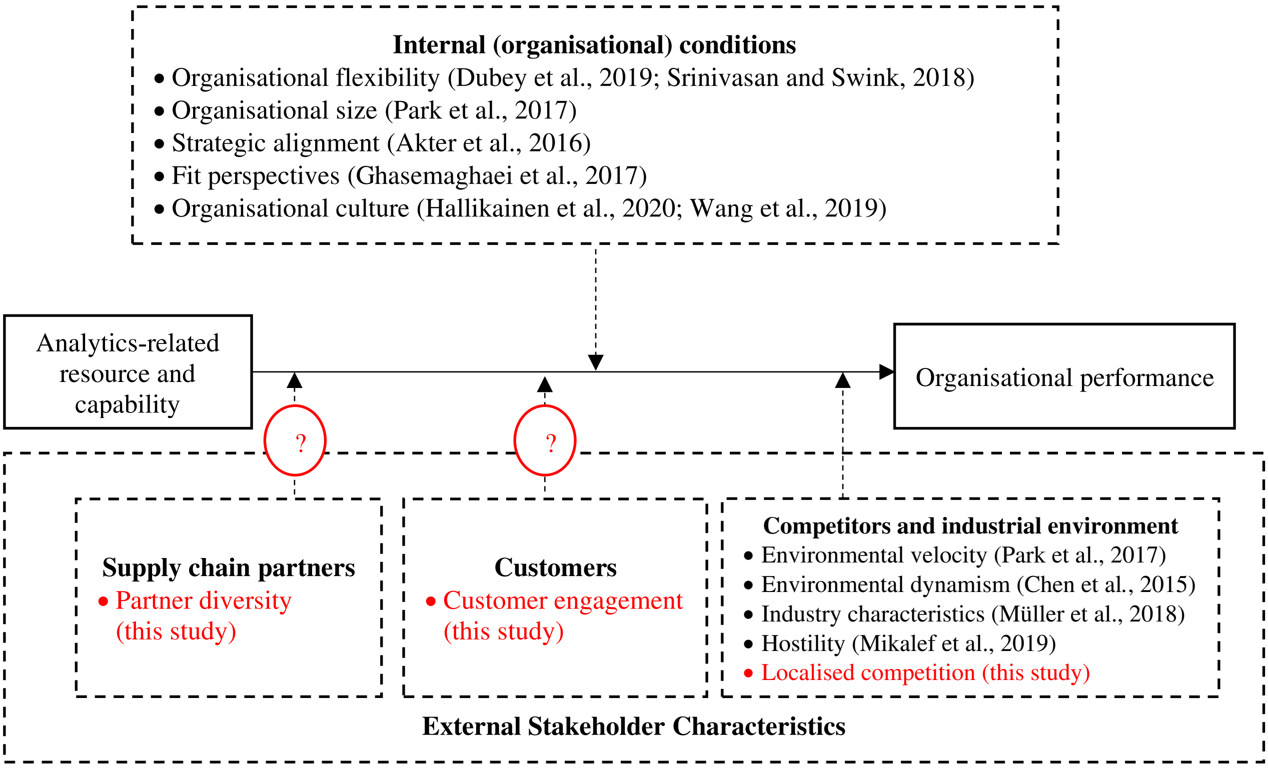


Figure 1. Visualising the research gaps in the current literature regarding the moderating role in the analytics-related resource and capability–organisational performance link

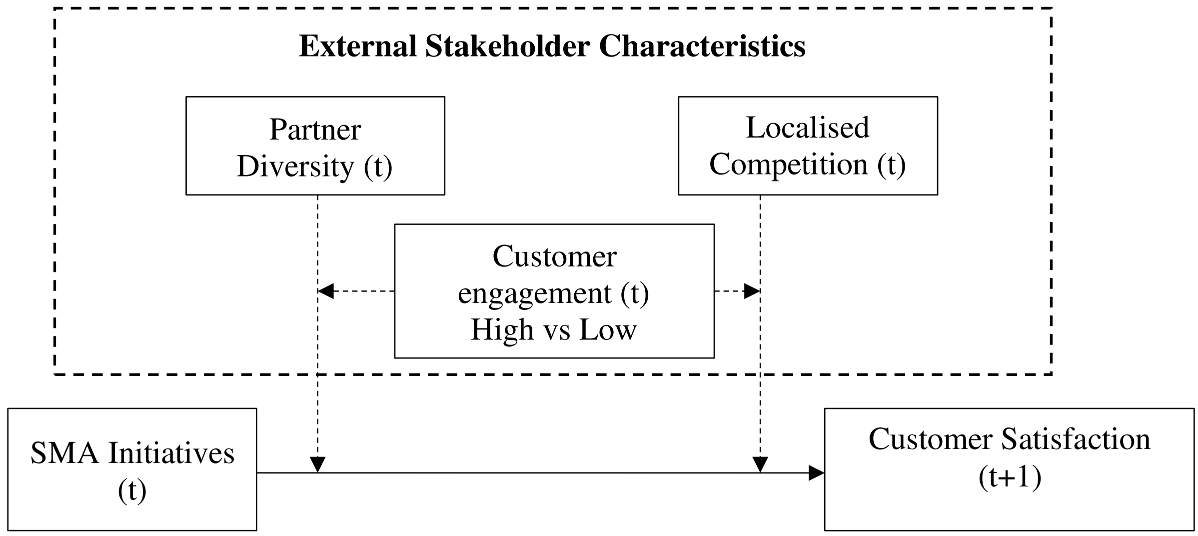
2.2. *The characteristics of external stakeholders on SMA implementation*

Contingency Theory (CT) points out the importance of external business conditions in building firm capability and performance. The general hypothesis of CT is that the superior performance of a firm depends on the extent to which its internal features (e.g. adoption of the best practices) can match the situational demands of its external environment (Hofer, 1975; Roh *et al.*, 2016; Sousa and Voss, 2008). Underpinned by CT, IS literature emphasises that a good fit between new IT and dominant forces in the external environment are critical for a company's strategic change and sustained organisational performance (Xue *et al.*, 2012). The business value of IT has been theorised to be contingent upon various external business environments, such as the characteristics of trading partners and the velocity and dynamism of the industrial environment (Melville *et al.*, 2004; Pavlou and El Sawy, 2010). Likewise, OSCM literature claims that changing the conditions in the external environment (e.g. supplier and customer relationships) is necessary to build a more certain environment to support the growth of the firm (Boyd, 1990; Shu and Lewin, 2017). The survival and growth of a firm depend upon its ability not only to manage relationships with suppliers, customers or other organisations in the same industry that control needed external resources, but also to explore ways in which to "negotiate" the external environments.

These CT arguments could be extended by theorising SMA as an optimal IT solution to improve CS, but such positive effects on CS are expected to vary according to the particular external conditions and situations. In fact, although the impact of SMA on operational performance has been initially recognised in the literature, inappropriate deployment of SMA may disrupt firms' operation and customer service, and ultimately tarnish their brand reputation (Johnson *et al.*, 2017; Moe and Schweidel, 2017). For instance, the diversity of social media data across various business partners may hinder its integration into a firm's processes, while the volume and velocity of data may further complicate its deployment (Moe and Schweidel, 2017). Moreover, it is possible that the business value of SMA may not be realised since firms would pay less attention on developing analytical capability to compete with their rivals in a less competitive environment. Contrarily, in highly competitive environments, implementing SMA is necessary to optimise service operations and maintain competitiveness (Cohen, 2018).

To fully appreciate the effects of SMA, the contingency roles of partner diversity and localised competition need to be understood in relation to customer engagement, which has been widely regarded as an important strategic resource (Pansari and Kumar, 2017). We argue that the effects of partner diversity and the effects of competitions can be contingent on the level of customer engagement. Having highly engaged customers provides signals to those business partners about the importance of SMA usage and required commitment to help the focal company to deal with them (Guesalaga, 2016). In a highly competitive environment, companies with few engaging customers could face significant challenges to make sense of the market and the use of SMA could be inefficient, due to the difficulties in obtaining enough data from the customers.

Drawing upon the perspective of CT, we propose a theoretical model to comprehensively capture the interplay between internal contingency (i.e. implementation of SMA) and external contingencies. In particular, we consider how external stakeholder characteristics moderate the impact of SMA on CS. We focus on three external stakeholder characteristics, namely partner diversity, customer engagement and localised competition in this research because they represent the different roles of the external stakeholders (i.e. business partners, customers and competitors) for SMA implementation. Our research model is shown in Figure 2 and the associated hypotheses are discussed in the next section.



Dotted line indicates the moderating effect of SMA initiatives
t: Data collected June – July 2016
t+1: Data collected within a full one-year period from August 1st, 2017 to July 31st, 2018
Control variables: firm size, star rating, metropolitan hotel and chain hotel

Figure 2. Research Model

3. Hypothesis Development

3.1. The impact of SMA on customer satisfaction

Prior research has indicated that social media usage could benefit an organisation in various ways, for example by improving CS (Gu and Ye, 2014; Ramanathan *et al*., 2017) and customers' perceptions toward quality (Gao *et al.*, 2015) and by enhancing operational efficiency (Cui *et al.*, 2018; Lam *et al.*, 2016). The use of social media has become a core initiative of the evolving digitalisation of business (Cohen, 2018). To dig out the business value from social media data, firms require SMA. According to Xiang *et al.* (2017), SMA is *"concerned with using analytical tools and frameworks to collect, analyse, summarise and interpret social media data to extract useful patterns and insights"*. SMA initiatives can be conceptualised into three categories based on the SMA process (Fan and Gordon, 2014): (1) aggregation; (2) analysis; and (3) interpretation.

Aggregation initiative refers to the transformation of diverse types of social media data into a format that can be read and analysed by the data analysis platform. Aggregation initiatives (e.g. firms' ability to search out and select relevant user-generated ideas for innovation development) can mitigate information overload when processing a vast amount of user-generated content on social media channels, and thus improve the quality of business decision making (Dong and Wu, 2015). Firms are able to gain an overview of consumer feedback and word-of-mouth reflected by social media, which in turn allows them to take proactive actions to respond to customers' needs (Luo *et al*., 2013). Social media can reveal information about users' social influence, connections, networking structure and position in the social network that may help marketers identify potential customers and their preferences. For instance, Nam and Kannan (2014) find that tracking information contained in social tags can proactively improve brand performance and financial performance. The appropriate deployment of aggregation initiatives allows firms to seamlessly integrate social media data across multiple social networking sites, to effectively track social media events and customer engagement activities, and to search social networking sites for all data related to customer characteristics, thereby facilitating their CS.

Analysis initiative refers to the identification of customer needs through various analytical techniques based on the specific mechanisms used for analytics, which can then inform a firm's decisions and actions. In recent SMA studies, analytic initiatives have been considered as crucial components of SMA, which transform social media raw data into marketing insights. Analysis initiatives enable firms not only to analyse large amounts of online customer reviews to understand the past, current and future conditions regarding target customers, but also to exploit undetected correlations, patterns and trends between specific variables of interest across social networking sites, which, in turn, can improve a firm's brand sales (Lee and Bradlow, 2011; Liu and Toubia, 2018; Toubia *et al*., 2019).

Interpretation initiative refers to the production of business reports that evaluate customer service and identify areas for operational improvement. Interpretation initiatives allow firms to generate performance metrics in real-time or near-real-time, which can be presented in visual dashboards/systems for role-based decision-making and to provide actionable insights or recommendations in a format readily understood by social media managers. As social media can be a reliable indicator for predicting customer behaviour (Luo *et al*., 2013), and because incorrect interpretation of the outputs generated from SMA could result in questionable business decisions, the key to utilising social media metrics is to equip managers and data scientists with relevant professional competencies (Wang *et al*., 2018).

Taken together, the above SMA initiatives allow us to evaluate an organisation's analytic prowess, specifically how thoroughly that organisation has been transformed by better use of analytics and information. We argue that SMA are strategic resources that integrate the use of various social media with analytics approaches for service operations management. Prior research has shown that SMA initiatives provide an effective means for firms to obtain market knowledge and customer insights, which, in turn, helps firms to improve their current customer experience, retention and revenue (Moe and Schweidel, 2017). Hence, we argue that, with appropriate deployment, SMA initiatives have the potential to transform social media data into a vital source of insights that can be used to improve CS. Therefore, we propose the following hypothesis:

Hypothesis 1 (H1): Social media analytics initiatives have a positive effect on customer satisfaction.

3.2. The contingent role of external stakeholder characteristics

Partner diversity refers to *"the degree of heterogeneity in the types of partners with which a firm allies"* (Terjesen *et al*., 2011, p. 107). The extent to which a firm selects business partners for collaboration has been a subject of much debate in the OSCM literature. High partner diversity is likely to gain a higher bargaining power within the complex network of supply chains (Raguseo *et al*., 2007; Ling *et al*., 2014), to complement a focal firm's knowledge and tacit skills that are required to achieve innovation (Van Beers and Zand, 2014), and to build supplier innovation triads (Potter and Paulraj, 2020). Nevertheless, high partner diversity within the supply chain network may come with additional overhead costs, and some concerns about channel conflicts and data governance. As Steven *et al*. (2014) suggest, a complex supply chain network where a large number of suppliers are involved may lead to "upstream complexity" issues in the supply chain, such as increasing the difficulty of monitoring supplier behaviour. Due to such increased complexity, companies are likely to face supplier risk and lower supplier responsiveness (Choi and Krause, 2006). Saboo *et al*. (2017) further indicate that firms that focus on many supply chain partners will be less capable of managing the relationship and the increasing transaction costs.

Put into our research context, hotels heavily rely on SMA to deal with social media data, such as review aggregators of travel-related content, booking preferences and patterns generated from their business partners to optimise service operations (Cohen, 2018). Where hotels have a close partnership with a few selected business partners, and therefore the partner diversity is low, hotels should be capable of accessing high quality social media data from its partners and the information sharing between the hotel and other partners should be more accurate (Steven *et al*., 2014). Conversely, hotels with high partner diversity will need to invest more resources to build strong SMA capability to address consumer needs due to the complexity of social media data governance. Ye *et al*. (2018) argue that working closely with a large variety of hotel partners, such as online travel agents, is not a guarantee of sales growth. Hence, we argue that with lower partner diversity, hotels can more easily manage the necessary resources (such as customer profiles and daily transaction data) to strengthen the effectiveness of SMA in achieving superior CS. We hypothesise that:

Hypothesis 2 (H2): The extent to which a firm develops its SMA initiatives has a stronger effect on customer satisfaction when partner diversity is low than when it is high.

Localised competition refers to the intensity of competition among organisations in a particular geographic area (Baum and Mezias, 1992). In the hospitality sector, localised competition has been widely acknowledged as one of the most important factors influencing hotels' market position and marketing strategy, because location is a crucial criterion affecting travellers' purchasing decisions (Chung and Kalnins, 2001). Hotels normally compete with either neighbouring competitors within a relatively well-defined geographic area, or those with proximate class and market position (Chung and Kalnins, 2001). When the potential for intense competition increases, hotels may face market uncertainty or unpredictability. In this case, they would adopt new technology or innovation in order to overcome challenges and threats in the market.

The impact of competition intensity on organisational IT adoption and innovation has been well documented in IS (e.g. Chatterjee *et al.*, 2002; Zhu and Kraemer, 2005) and OM (e.g. Lam *et al.*, 2019) studies. In an environment of high competition, firms are more likely to devote greater analytical effort to explore new business opportunities and overcome market threats. This is because the deployment of data analytics is inherently linked to the exploration of opportunities, satisfaction of demand and utilisation of resources within a business environment (Park *et al.*, 2017). Kitchens *et al.* (2018) suggest that analytical capability can be improved in high-volume data environments because analytics requires substantial data from stakeholders such as competitors to make an accurate analysis, and mature analytical processes to achieve superior performance. Hence, it is possible that SMA will create more operational benefits for hotels operating in local markets with high levels of geographical competition, since there would be more demand for, and more opportunities to support, the use of analytics.

In contrast, in less competitive environments firms would avoid excessive investment and risk taking and would pay less attention to developing their analytical capability. Therefore, the intention to adopt new advanced technologies such as SMA for firm growth will be reduced when focal firms face low competition from their local rivals (Xue *et al.*, 2012). Consequently, localised competition is considered as a condition of competitor within the industrial environment that positively moderates the relationship between SMA and CS, such that the impact of SMA on CS will be higher for firms operating in markets where there is a high level of geographically localised competition. We hypothesise that:

Hypothesis 3 (H3): The impact of SMA initiatives on customer satisfaction is higher for firms operating in a highly competitive geographical environment.

Customer engagement can be defined as *"the mechanics of a customer's value addition to the firm, through direct or/and indirect contribution"* (Pansari and Kumar, 2017, p. 295). It is more likely that firms, who are able to establish a continuing dialogue with customers, to create knowledge that is then shared among groups of customers with shared interests, and even extend the interactions to competitors' customers or prospective customers on the internet, will gain more benefits from social media (Sawhney *et al.*, 2005). Engaging customers to collaborate with firms in the value adding process could better satisfy their needs as well as the needs of other customers. Promoting SMA in a firm could be resource demanding. Firms not only need to invest in the analytics platforms and human resources for data mining, monitoring and interpretation, but must also sustain a close collaboration with business partners, who may share the social media data from different platforms (Steven *et al.*, 2014). Where partner diversity is low, the company will be better able to maintain close collaboration and ensure the data quality. Firms with higher customer engagement inherently have more diverse online information and more complex social media data (Carlson *et al.*, 2018). This may make it more difficult for firms that have greater level of partner diversity to apply SMA.

On the other hand, having higher customer engagement signals the popularity of the companies and would therefore help to increase their bargaining power with business partners (Pansari and Kumar, 2017). If the highly customer-engaged firms collaborate with only a limited number of partners, they are more likely to gain valuable customer insights and better-quality data, as the business partners need to get support of these firms. Hence it is likely that, with low diversity of partners and close partnership between business partners and focal firms, higher customer engagement will be more beneficial in facilitating the SMA–CS relationship.

Hypothesis 4 (H4): Where there is high customer engagement, the impact of SMA initiatives on customer satisfaction will be strengthened when the partner diversity is low.

Engaging customers on social media platforms enhances the efficiency of communication, and thus the intimacy with those customers and promotes customers' future intention to use the service or to purchase products (Simon and Tossan, 2018). These benefits are important when SMA is being employed to facilitate aspects of company performance such as word-of-mouth and customer perceived quality. SMA provides the valuable customer insights and market knowledge necessary for the improvement of such company performance, while high customer engagement ensures that social media data are updated frequently and that the norms of high-quality communication among loyal customers or fans are maintained. It is likely that the benefits of pairing SMA with customer engagement as a means to enhance CS will be enhanced among firms operating in more competitive local environments. In a local market characterised by intense competition, firms could face the challenges of managing unpredictable demand and pressure created by online visibility. Companies operating in intensively competitive environments require higher levels of information-processing capability from their IT adoption. However, where there is low customer engagement, firms may increasingly struggle to make sense of the market, with the lack of sufficient information decreasing the effectiveness of SMA. Hence:

Hypothesis 5 (H5): Where there is high customer engagement, the impact of SMA initiatives on customer satisfaction will be stronger for firms operating in a highly competitive geographical environment.

4. Research Methods

4.1. Sampling and data collection

The targeted respondents were managers of hotels located in Greece. To obtain a representative sample, we identified the hotels in the Attica region from the Hellenic Chamber of Hotels (HCH) database, which provides the hotel profile and contact information for all the certified hotels in Greece. Initially, a full contact list of 648 hotels was identified. After removing the entries with missing e-mail addresses, the total usable number of hotels for further research was 550. Finally, 158 responses were received from an online questionnaire platform. Therefore, the questionnaire response rate was 28.73%. The CS data of each hotel were captured from TripAdvisor. After taking account of data missing from TripAdvisor, our final effective sample consisted of 141 firms. The demographic characteristics of the respondents and hotel profiles in our effective sample are shown in Table 1.

To examine the non-response bias, we conducted independent sample *t*-tests between the response group (n=158) and non-response group (n=392) in terms of hotel star ratings. The results of both tests were insignificant, thus indicating that non-response bias is not a threat to this research. Similarly, we used the *t*-test to check whether male-female respondents and junior-senior respondents perceived constructs in the same way. The results indicate that there is no significant difference in perception of the proposed constructs and variables across the gender groups and age groups.

Table 1. Respondents' characteristics (N = 141)

Demographic traits		Frequency	Percentage (%)
Gender	Male	76	53.9%
	Female	65	46.1%
Age	18-24	24	17.0%
	25-35	47	33.3%
	36-45	37	26.3%
	46-55	23	16.3%
	56-65	10	7.1%

Number of employees	1-20	63	44.7%
	21-40	55	39.0%
	41-60	17	12.0%
	61-80	6	4.3%
Star rating	1-Star	9	6.4%
	2-Star	27	19.1%
	3-Star	43	30.5%
	4-Star	43	30.5%
	5-Star	19	13.5%
Geographical location	Metropolitan	94	66.7%
	Rural area	47	33.3%
Hotel group	Independent hotel	107	75.9%
	International chain	34	24.1%

4.2. Measures and control variables

***SMA initiatives*.** As shown in Table 2, the measures of SMA initiatives consist of six questionnaire items from the existing literature (Wang and Byrd, 2017). The independent measures are assessed on a 5-point Likert scale to capture the respondents' agreement level on their SMA initiatives from the perspectives of data aggregation (SMA1 and SMA2), data analysis (SMA3 and SMA4) and data interpretation (SMA5 and SMA6). The data collection process lasted approximately 2 months (June 2016 – July 2016). Because our research targets were hotel managers in Greece, it was important to carefully refine and translate all the question items and definitions into Greek. Following Brislin (1970), we adopted a back-translation approach to ensure conceptual equivalence. The confirmatory factor analysis (CFA) results for the SMA initiatives scales reveals satisfactory measurement model fit indices: $\chi_2(8)= 16.477$, comparative fit index (CFI) = .91, Tucker-Lewis index (TLI) = .82, and RMSEA = .05 (Bagozzi and Yi, 2012). We also obtained convergent validity for SMA initiatives, as factor loadings meet the criterion of O'Rourke and Hatcher (2013) (Table 2). Average variances extracted (AVE) is 0.561 and composite reliability is 0.884, indicating adequate reliability.

***Customer satisfaction*.** CS is a surrogate measure of competitive advantage (Katsikeas *et al*., 2016). The dependent variable is measured by average sentiment value of the hotel review. We obtained the archival data from TripAdvisor one year after the completion of questionnaire data collection (i.e. August 1st, 2017 to July 31st, 2018). In particular, we conducted a lexicon-based sentiment analysis to calculate the average sentiment value of the hotels' reviews (Taboada *et al.,* 2011; Lee *et al*., 2018). In order to determine the polarity of the review comments, we annotated the comments using the dictionary from Hu and Liu (2004). Polarity is calculated for review comments showing how positive/negative a comment is.

***Partner diversity*.** This variable refers to the level of presence and visibility on online travel agents (OTAs)' websites for a hotel. Following Rafuseo *et al.*'s (2007) suggestion, we measure it by the number of OTAs over which a focal hotel is listed and sells rooms out of a list of 12 key OTAs[1] that cover hotels operating in Greece. The list encompasses three predominant business models used by the OTAs, namely the merchant model (e.g. Hotels.com and Lastminute.com), the agency model (e.g. Trip.com and zenHotel) and the advertising model (e.g. FindHotel and HotelsCombined). The number of OTAs ranges from 0 to 12. We checked the timestamp of the first customer review posted on each OTA website to ensure that the number of OTAs for each hotel reflects the situation in July 2016. Due to the complexity of the data and the variety of OTA channels, the data collection was a labour-intensive task. We recruited three research assistants to carry out the coding task and perform the cross-check of the data validity. To ensure data quality and consistency among research assistants, we developed a standardised data collection procedure and instruction for training and continuing guidance. All the samples collected were further verified by our research team.

***Localised competition*.** A postcode area in Greece is the geographic area that corresponds to the five digits of a postcode. The first three digits of a postcode refer to a particular region (in this case the Attica region), whilst the last two digits refer to a particular part of that region (for example, Athens). As suggested by Chung and Kalnins (2001), we counted the number of competing hotels with similar size operating in the same postcode area. Using PKF Consulting's (1997) hotel classification, hotel size was categorised into three size classes ranging from small (fewer than 124 guest rooms), to medium (125 to 200), to large (more than 200). Where a postcode area contains a high number of active hotels of similar size, we consider that there is a high level of localised competition.

***Customer engagement*.** In this study, for reasons of data availability, the measurement of customer engagement focuses on both customer contribution and customer creation behaviours (Schivinski *et al.*, 2016). A composite variable of customer engagement was computed by a natural logarithm of the mean score of proxies representing consumer creation and contribution behaviours. Following Liu *et al.* (2019), we adopted a commonly-used additive aggregation method to calculate the average of multiple indicator variables. More

[1] Expedia group (Hotels.com /Travelocity/ Orbitz.com/Trivago), Lastminute.com, Agoda, Trip.com group (trip.com/skyscanner), Travel Republic, Hotel Reservation Service, zenHotel, Booking holding group (Booking.com/Priceline), Ebookers.ie, FindHotel, HotelsCombined, and KAYAK

specifically, we used the sum of the number of "helpful" votes on comments posted by customers and presented on the hotel's TripAdvisor page by the end of July 2016 as a proxy of contribution behaviours. As proxy for the creation type of customer engagement, we used the total number of comments posted by customers on TripAdvisor by the end of July 2016.

Control variables. In this study we considered four control variables; namely, the *firm size, star rating, metropolitan hotel* and *chain hotel*, because of their potential impact on our dependent variables. Various studies have revealed the significant impact of star rating on hotel customer satisfaction (e.g. Radojevic *et al.*, 2015; Zhao *et al.*, 2019). We predict the relationship will be positive as higher rated hotels generally offer better quality service and product to the customers. For metropolitan hotels, we used a dummy variable to indicate whether the hotels were operating in the metropolitan area (e.g. the city of Athens), because the customers might be more satisfied with the hotels with convenience location. We also controlled for a dummy variable of indicating whether the observation is a chain hotel, because capabilities and organisational performance are expected to be diverse across the chain hotel and other hotels (Banerjee and Chua, 2016). As shown in Table 2, firm size is taken as the ordinal variable of the number of employees (Thao *et al.*, 2019). Based on prior studies, we expect that firm size and chain hotel are negatively associated with CS, as a large-scale hotel could be lack of flexibility to deal with customer complaints and it may offer more standardized products and services at lower prices (Assaf *et al.*, 2015; Menicucci, 2018).

Following the guidance of Hulland *et al.* (2018), to limit the common method variance (CMV) bias we adopted a design using multisource data for all the variables. To further control CMV, we used both subjective and objective measures of our focal variables in the model. All the measures adopted in this study are listed in Table 2 and Table 3 show their descriptive statistics and correlation matrix.

Table 2. Measurement of variables

Variables	Measurement	Data Source	Reference
Customer Satisfaction (DV)	Calculate the average sentiment value of the hotels' reviews using lexicon-based sentiment analysis	TripAdvisor	Taboada et al. (2011); Lee et al. (2018)
SMA initiatives (IV)	Five-point Likert scale is used to capture the respondents' agreement level on the following items (factor loadings are in brackets):	Primary data	Wang and Byrd (2017)

	SMA1: Collect data (e.g., customer reviews) from social networking sites or travel websites (.774) **SMA2:** Store data collected from social media in appropriate databases (.688) **SMA3:** Identify important business insights to improve services (.736) **SMA4:** Analyse social media data to understand current trends among a large population (.737) **SMA5:** Provide systematic and comprehensive reporting to help recognise feasible opportunities for service improvement (.762) **SMA6:** Provide near-real time or real time information on day-to-day hotel services (.793)		
Partner diversity (M)	The number of OTAs on which a hotel is listed and sells rooms out of a list of 12 players[2] that cover hotels in Greece.	OTAs' websites	Ling et al. (2014); Raguseo et al. (2017)
Localised competition (M)	The number of similar competitors located within the same post code.	HCH database	Chung and Kalnins (2001)
Customer engagement (M)	Natural logarithm of the mean score of proxies representing consumer creation (the number of reviews) and contribution (the number of 'helpful' votes) behaviour presented on the hotel's TripAdvisor page by the end of July 2016.	TripAdvisor	Liu et al. (2019); Schivinski et al. (2016)
Firm Size (C)	Ordinal variable of the number of employees: 1=1-20; 2=21-40; 3=41-60; 4=61-80	HCH database	Thao et al. (2019)
Star rating (C)	Hotel class segmentation information about each hotel being reviewed using a service segmentation scheme that classifies hotels using "Crowns" with the value ranging from 1 to 5.	TripAdvisor	Xie et al. (2016)
Metropolitan Hotel (C)	A dummy variable indicating the metropolitan hotel, otherwise equals to zero.	HCH database	Yang et al. (2014)
Chain Hotel (C)	A dummy variable indicating the chain hotel, otherwise equals to zero.	HCH database	Banerjee and Chua (2016)

[2] Expedia group (Hotels.com /Travelocity/ Orbitz.com/Trivago); Lastminute.com; Agoda; Trip.com group (trip.com/skyscanner); Travel Republic; Hotel Reservation Service; zenHotel; Booking holding group (Booking.com/Priceline); Ebookers.ie; FindHotel; HotelsCombined; KAYAK.

Table 3. Correlation Matrix

Variables	Mean	Std. dev.	1.	2.	3.	4.	5.	6.	7.	8.	9.
1. Firm Size	1.760	0.827	1								
2. Star Rating	2.404	1.276	-.0137	1							
3. Metropolitan Hotel	0.667	0.473	0.176*	-0.024	1						
4. Chain Hotel	0.241	0.429	-0.016	-0.166*	0.117	1					
5. Partner Diversity	8.163	1.988	0.154	-0.271**	0.233**	0.113	1				
6. Localised Competition	8.830	1.232	.043	-0.188*	0.228**	0.048	0.164	1			
7. Customer Engagement	3.349	1.330	.290**	-0.155	0.258**	0.145	0.403**	0.110	1		
8. SMA	2.583	0.923	.241**	-0.035	0.181*	0.102	0.262**	0.131	0.299**	1	
9. CS	1.077	0.658	-.035	-0.031	-0.249**	-0.053	0.031	-0.075	0.342**	0.236**	1
Note: *p<0.05; **p<0.01 (two-tailed tests)											

4.3. Hypothesis testing

In order to test the causalities among the conceptual constructs, this study applied the structural equations modelling (SEM) approach. The advantages of using SEM over other similar analysis approaches, such as ordinary least squares regression is well documented (Sardeshmukh and Vandenberg, 2017). As this study investigates SMA as a latent construct that consist of five different question items, the use of SEM is justified (Bollen, 1989). In addition, SEM permits the incorporation of measurement error into the analysis (Kaplan, 2000).

The control variables of firm size and metropolitan hotels are significant and exhibit the expected directionality on CS, while the variables of star rating and chain hotel are insignificant. As shown in Table 4, the main effects of SMA on CS ($\beta = 0.562$, $p < 0.001$) are positive and significant, as expected. Therefore, H1 is supported. The interaction effects between the partner diversity and SMA on CS are significant and negative ($\beta = -0.207$, $p < 0.001$). This result supports H2: with increased diversity of business partners, the positive impact of SMA on CS will be weaker. Then, we tested the interaction effects between SMA and localised competition on CS ($\beta = 0.216$, $p < 0.001$). The interaction effects on both dependent variables are significant and positive. In this case, the result supports hypothesis (H3), which predicts that for firms operating in a highly competitive geographical market, the positive impacts of SMA on CS are stronger. The goodness-of-fit statistics indicate a good model fit for the structural model (NNFI = 0.901, IFI = 0.919 and CFI = 0.908), which exceeds the recommended threshold value of

0.90 (Cao and Zhang, 2011). The RMSEA is 0.037, which is below the acceptable maximum level of 0.08 (Browne and Cudeck, 1992).

To examine the contingency effects of customer engagement on all the hypothesised interaction effects among partner diversity, localised competition and SMA, we created a two-group model by dividing the sample into high (n = 70) and low (n = 71) customer engagement groups, based on the median of customer engagement (Wong *et al.*, 2011). As shown in Table 5, we have obtained significant X_2 difference (ΔX_2 with $p < 0.05$) result between the baseline model and the constrained model of which structural parameters constrained to be equal across high and low customer engagement group. This suggests variance of the model under high and low customer engagement (Wong *et al.*, 2011). More specifically, the relationship between the interaction effect (partner diversity x SMA) and CS is insignificant under low customer engagement ($\beta = 0.023$, *n.s.*) but negative and significant under high customer engagement ($\beta = -0.657$, $p < 0.01$) with a significant X_2 difference. These results suggest that the negative interaction effect between partner diversity and SMA is strengthened under high customer engagement, and hence supports H4. In addition, the interaction effect between localised competition and SMA on CS is insignificant under low customer engagement ($\beta = 0.058$, *n.s.*) but positive and significant under high customer engagement ($\beta = 0.545$, $p < 0.01$). This finding provides support for H5 that the positive interaction effect between localised competition and SMA on CS is strengthened under high customer engagement. A significant difference of the X_2 statistics also suggests variance of the interaction path across high and low customer engagement.

Table 4. Structural model

	Path Coefficient	Standard error	*t*-statistics	*p*-value	Hypothesis (Result)
Controls					
Firm size	-0.077	0.056	-1.564	0.00**	
Star rating	-0.026	0.036	-0.517	0.527	
Metropolitan Hotel	0.245	0.097	4.964	0.00**	
Chain Hotel	-0.055	0.107	-1.105	0.248	
Main Effect					
SMA initiatives	0.562	0.078	7.865	0.00**	H1 (Support)
Interaction effects					
Partner Diversity	-0.050	0.023	-1.020	0.340	
Localised Competition	-0.044	0.006	-0.889	0.316	
SMA x Partner Diversity	-0.207	0.006	4.186	0.00**	H2 (Support)
SMA x Localised Competition	0.216	0.005	4.398	0.00**	H3 (Support)
* p<0.05; ** p<0.01					

Table 5. Multi-group analysis for customer engagement (CE)

Models	$x2$	df	$X2/df$	$\Delta X2$	Δdf	X^2 difference test	High in CE	Low in CE	Hypothesis (Result)
1. Baseline Model	253.114	70	3.62						
2. Constrained Model	428.121	101	4.24	175.007	31	p<0.001			
3. Constrained Paths									
3a. Partner Diversity x SMA→ CS	259.084	71	3.65	5.970	1	p<0.05	(-0.657) **	(0.023) *n.s.*	H4 (Support)
3b. Localised Competition x SMA→CS	261.332	71	3.68	8.218	1	p<0.05	(0.545) **	(0.058) *n.s.*	H5 (Support)
Part Coefficient are in brackets; * p<0.05; **p<0.01; n.s. not significant									

5. Discussion and Conclusions

Based on the primary data from 141 hotels in Greece and their archival data from multiple sources, we employed structural equation modelling to examine the impact of SMA on CS and how the moderating roles of external stakeholder contribute to this association. The results show the positive impact of SMA initiatives on CS and further reveal that the impact of SMA initiatives on CS is significantly moderated by partner diversity, customer engagement and localised competition. The empirical evidence presented, interpreted through the lens of CT, provides novel insights and important implications for research and practice to the business analytics stream of OSCM literature, as discussed below.

5.1 Theoretical contributions

In the field of OSCM there is increasing interest in understanding the impact of SMA on service operations. This study responds to the call of Lam *et al.* (2016) to take into account how the SMA–CS relationship changes, while considering various characteristics of external stakeholders, in order to give a complete picture of SMA implementation. While a great deal of research focuses on user behaviours on social media from the customer perspective, few studies consider SMA as a strategic action at the firm level. We thus take an OSCM perspective to explore the possibility that SMA initiatives can be strategically deployed by firms to achieve positive effects on CS. Our results show that firms that invest in SMA could improve their CS. Consistent with the previous arguments, our results suggest that SMA initiatives are an effective way for firms to transform online customer opinions into marketing and service improvement insights (Lee and Bradlow, 2011; Toubia *et al.*, 2019).

Previous studies have made some attempts to examine different environmental factors that might moderate the impact of analytics on firms' performance. Yet, the role of external stakeholders has been overlooked when implementing analytics within organisations. We employ the lens of CT with the objective of examining how external stakeholder characteristics might amplify or lessen the positive effect of SMA on CS. This examination contributes to the literature on business analytics in the OM context and contingency theory in three ways. First, contrary to popular belief, our empirical findings suggest that under conditions of low partner diversity, the effect of SMA on CS is amplified. This is justified since cooperation with selected major partners within supply chain networks may ease the efforts in coordinating or enforcing the partners for data or information sharing (Steven *et al.*, 2014), and managerial insights may be easily explored from all relevant information accordingly. This finding not only adds new knowledge on the ongoing debate on whether the diversity of business partners is beneficial for firms who implement new IT to maintain competitiveness (Saboo *et al.*, 2017) but also addresses the limitations of merely focusing on environmental factors. This also encourages future research to explore the roles of other characteristics of firms' business partner.

Second, the significant moderating effect of localised competition indicates that SMA is differently valuable in improving CS under different competitive environments. We find that, specifically, under circumstances of greater levels of localised competition, strong SMA capabilities are particularly important for the improvement of CS. This result corroborates the existing literature on the positively moderating effect of highly competitive industries in the relationship between BDA assets and business value (Müller *et al.*, 2018). It is also aligned with the propositions of CT about the importance of understanding the interplay between the implementation of BDA and the external business environment (Grover *et al.*, 2018). We believe this finding is beneficial to both IS and OSCM research by revealing that before committing to any IT investment, firms need to examine its external business environment (Chen *et al.*, 2014).

Third, interestingly, we found that where there is high customer engagement, the impact of SMA on CS could be strengthened when the partner diversity is low or localised competition is high. This finding advances the OSCM literature by reinforcing the need for managing well the relationship with customers, as investing in SMA when having high partner diversity or low localised competition is unlikely to result in superior CS. The discovery of the moderating role of customer engagement should be beneficial to future contingency research for explaining the performance variation due to the interaction between customer-related contingencies and other environmental contingencies.

5.2 Practical implications

Firms have been acknowledged to exhibit greater appreciation that SMA brings value to their customer service and operation; however, the business value of SMA is not directly achieved. Some practitioners remain unsure how best to deploy their SMA initiatives and to make them pay off, and this may disrupt the profitability of SMA investment. Our research provides four concrete implications that may guide their current or future SMA execution.

First, we find support for the result that SMA initiatives are crucial strategic actions that directly impact CS. In particular, the aggregation, analysis and interpretation initiatives identified in this study can serve as a guideline in assessing the deployment of SMA initiatives. The responsibility to optimise SMA deployment lies entirely with the managers – it is their duty to understand whole social media data life cycle that starts with data aggregation, proceeds via specific function of data analysis, and culminates with data interpretation. Prioritising this task in SMA will enable a firm to transform social media data into meaningful business insights for improving CS. These SMA initiatives of course need to be in conjunction with a set of data governance procedures, and importantly the value realized from SMA is subject to the characteristics of external environment and stakeholder.

Second, we show that low diversity of business partner collaboration might create more SMA's value potential. This finding is in contrast to the recent literature that has strongly emphasised that high level of partner diversity is preferred for the creation of business value (Alonso and Andrews, 2019; Potter and Paulraj, 2020). We caution that practitioners should not entirely follow the recent mantra; rather, when optimising SMA, they are advised to adopt a selective distribution strategy in which a limited number of business partners are chosen for partnership. Put into our research context, hotels take advantage of real-time data to detect patterns and discover business insights from business partners to improve operational processes and efficiencies. Without consistency and compatibility of the data that are collected across various business partners' systems (e.g. booking system and customer ratings and reviews system), hotels may struggle to make good use of SMA. The vast amounts of data being captured from a large number of business partners may pose a challenge to accurate prediction of operations and processes, since analytics relies on the high quality and high integration of data (Wang *et al.*, 2018). As such, we believe that hotels that are exposed to high partner diversity may suffer from fragmentation and inaccuracy of data collection, which would impede the effectiveness of SMA. Consequently, our results provide important insights for hotel managers in terms of signalling the negative consequences of partner diversity during the deployment of SMA.

The third practical implication of this study regards the impact of SMA on CS in different business environments. In a highly competitive environment, SMA would be more efficient in enhancing CS. In the light of this finding, practitioners engaged in the development of SMA should focus strongly on the efficiency of operations that are aligned with the environmental context of the hotel. Specifically, when evaluating the returns from SMA, practitioners need to be cognizant of the existing and future states of the local market environment in which the hotels operate (Melville *et al.*, 2004).

Fourth, practitioners should understand that overlooking customer engagement may lead to an incomplete picture of SMA deployment. More specifically, the results of our moderated moderation analysis reveal that when high customer engagement is achieved, the adoption of a low partner diversity strategy or the presence of high localised competition further strengthen the positive impact of SMA initiatives on CS. In contrast, if firms have lower customer engagement on social media, even having a high level of SMA in the centralised partner network and responding to the intensively competitive environment may not result in good customer satisfaction. In this sense, when practitioners consider initiating SMA, it is critical to evaluate their current state of customer engagement.

5.3 Limitations and future research

This study suffers from several limitations; however, these indicate directions for future research. The first and most significant limitation is that the single country and industry context of this study hinders the generalisability of its findings. Therefore, it would be worthwhile for future research to increase the scope of observation to further validate our findings by using samples from different research contexts in a broader range of countries and industries.

Second, the selected measurement of the CS is representative and valuable for achieving the objectives of this research, and it allows for results that do not suffer from methodological bias, such as common method variance. However, the set of measurement we selected is not able to provide a perfectly comprehensive picture. This could be addressed in future research by adding more variables to capture different dimensions of firm performance, such as financial performance or actual sales.

Third, in common with other researches that utilise primary data, the proxies of SMA initiatives were measured by data obtained from the hotel managers' responses. However, there might be a gap between the disclosure of SMA projects and real SMA practices. How to use secondary data from other sources to measure the SMA could be a worthwhile topic for future studies.

Finally, regarding the empirical research design, due to the cross-sectional nature of this study the findings cannot be taken as conclusive evidence of the hypothesised relationships. Specifically, our analysis took into consideration only the data for a certain period time (t in 2016 and t+1 from 2017 to 2018). We recommend that future research should adopt a longitudinal research design or re-examine the underlying causal relationship through panel data. Nevertheless, given that we utilised a reasonably large sample size in comparison with other similar studies and take into consideration multiple data sources, this study does provide a solid basis for understanding the SMA–CS relationship and the moderating role of external stakeholder characteristics on this relationship.

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References

Abrahams, A. S., Fan, W., Wang, G. A., Zhang, Z. and Jiao, J. (2015). "An integrated text analytic framework for product defect discovery", *Production and Operations Management*, Vol. 24 No. 6, pp. 975-990.

Akter, S., Wamba, S.F., Gunasekaran, A., Dubey, R. and Childe, S.J. (2016). "How to improve firm performance using big data analytics capability and business strategy alignment?", *International Journal of Production Economics*, Vol. 182, pp. 113-131.

Alonso, J. M. and Andrews, R. (2019). "Governance by targets and the performance of cross-sector partnerships: Do partner diversity and partnership capabilities matter?", *Strategic Management Journal*, Vol. 40 No. 4, pp. 556–579.

Assaf, A. G., Josiassen, A., Cvelbar, L. K. and Woo, L. (2015). "The effects of customer voice on hotel performance", *International Journal of Hospitality Management*, Vol. 44, pp. 77-83.

Bagozzi, R. P. and Yi, Y. (2012). "Specification, evaluation, and interpretation of structural equation models", *Journal of the Academy of Marketing Science*, Vol. 40 No. 1, pp. 8-34.

Banerjee, S. and Chua, A. Y. (2016). "In search of patterns among travellers' hotel ratings in TripAdvisor", *Tourism Management*, Vol. 53, pp. 125-131.

Baum, J. A. and Mezias, S. J. (1992). "Localized competition and organizational failure in the Manhattan hotel industry 1898-1990", *Administrative Science Quarterly*, Vol. 37 No. 4, pp. 580-604.

Bollen, K. (1989). Structural equations with latent variables. New York, NY: John Wiley.

Boyd, B. (1990). "Corporate linkages and organizational environment: A test of the resource dependence model", *Strategic Management Journal*, Vol. 11 No. 6, pp. 419-430.

Brandon-Jones, A., Lewis, M., Verma, R. and Walsman, M. C. (2016). "Examining the characteristics and managerial challenges of professional services: An empirical study of management consultancy in the travel, tourism, and hospitality sector", *Journal of Operations Management*, Vol. 42, pp. 9-24.

Brislin, R. W. (1970). "Back-translation for cross-cultural research", *Journal of Cross-cultural Psychology*, Vol. 1 No. 3, pp. 185-216.

Browne, M. W. and Cudeck, R. (1992). "Alternative ways of assessing model fit", *Sociological Methods & Research*, Vol. 21 No. 2, pp. 230-258.

Cao, M. and Zhang, Q. (2011). “Supply chain collaboration: Impact on collaborative advantage and firm performance”, *Journal of Operations Management*, Vol. 29 No. 3, pp. 163-180.

Carlson, J., Rahman, M., Voola, R. and De Vries, N. (2018). “Customer engagement behaviours in social media: capturing innovation opportunities”, *Journal of Services Marketing*, Vol. 32 No. 1, pp.83-94.

Chan, H. K., Wang, X., Lacka, E. and Zhang, M. (2016). “A mixed-method approach to extracting the value of social media data”, *Production and Operations Management*, Vol. 25, No. 3, pp. 568-583.

Chatterjee, D., Grewal, R. and Sambamurthy, V. (2002). “Shaping up for e-commerce: Institutional enablers of the organizational assimilation of web technologies”, *MIS Quarterly*, Vol. 26 No. 2, pp. 65–89.

Chen, D. Q., Preston, D. S. and Swink, M. (2015). “How the use of big data analytics affects value creation in supply chain management”, *Journal of Management Information Systems*, Vol. 32 No. 4, pp. 4-39.

Chen, Y., Wang, Y., Nevo, S., Jin, J., Wang, L. and Chow, W. S. (2014). “IT capability and organizational performance: the roles of business process agility and environmental factors”, *European Journal of Information Systems*, Vol. 23 No. 3, pp. 326–342.

Choi, T. Y. and Krause, D. R. (2006). “The supply base and its complexity: Implications for transaction costs, risks, responsiveness, and innovation”, *Journal of Operations Management*, Vol. 24 No. 5, pp. 637–652.

Chung, W. and Kalnins, A. (2001). “Agglomeration effects and performance: A test of the Texas lodging industry”, *Strategic Management Journal*, Vol. 22, No. 10, pp. 969-988.

Cohen, M. C. (2018). “Big data and service operations”, *Production and Operations Management*, Vol. 27 No. 9, pp. 1709-1723.

Cui, R., Gallino, S., Moreno, A. and Zhang, D. J. (2018). “The operational value of social media information”, *Production and Operations Management*, Vol. 27 No. 10, pp. 1749-1769.

Dong, J. Q. and Wu, W. (2015). “Business value of social media technologies: Evidence from online user innovation communities”, *The Journal of Strategic Information Systems*, Vol. 24 No. 2, pp. 113-127.

Dubey, R., Gunasekaran, A. and Childe, S. (2019). “Big data analytics capability in supply chain agility: The moderating effect of organizational flexibility”, *Management Decision*, Vol. 57 No. 8, pp. 2092-2112.

Fan, W. and Gordon, M. D. (2014). “The power of social media analytics”, *Communications of the ACM*, Vol. 57 No. 6, pp. 74-81.

Gao, G.G., Greenwood, B.N., Agarwal, R. and McCullough, J. (2015). “Vocal minority and silent majority: How do online ratings reflect population perceptions of quality?”, *MIS Quarterly*, Vol. 39, No. 3, pp. 565-589.

Ghasemaghaei, M., Hassanein, K. and Turel, O. (2017). “Increasing firm agility through the use of data analytics: The role of fit”, *Decision Support Systems*, Vol. 101, pp. 95-105.

Ghose, A., Ipeirotis, P. G. and Li, B. (2012). “Designing ranking systems for hotels on travel search engines by mining user-generated and crowdsourced content”, *Marketing Science*, Vol. 31 No. 3, pp. 493-520.

Gibb, G. (2015). How multi-channel analytics helps IHG understand its customers. Available at: https://www.ebiquity.com/news-insights/blog/how-multi-channel-analytics-helps-ihg-understand-its-customers/.

Gosling, J., Hewlett, B. and Naim, M. M. (2017). “Extending customer order penetration concepts to engineering designs”, *International Journal of Operations & Production Management*, Vol. 37 No. 4, pp. 402-422.

Grover, V., Chiang, R. H., Liang, T. P. and Zhang, D. (2018). “Creating strategic business value from big data analytics: A research framework”, *Journal of Management Information Systems*, Vol. 35 No. 2, pp. 388–423.

Gu, B. and Ye, Q. (2014). “First step in social media: Measuring the influence of online management responses on customer satisfaction”, *Production and Operations Management*, Vol. 23 No. 4, pp. 570-582.

Guesalaga, R. (2016). The use of social media in sales: Individual and organizational antecedents, and the role of customer engagement in social media. *Industrial Marketing Management*, Vol. 54, pp. 71–79.

Hallikainen, H., Savimäki, E. and Laukkanen, T. (2020). “Fostering B2B sales with customer big data analytics”, *Industrial Marketing Management*. Vol. 86, pp. 90-98.

Hazen, B. T., Boone, C. A., Ezell, J. D. and Jones-Farmer, L. A. (2014). “Data quality for data science, predictive analytics, and big data in supply chain management: An introduction to the problem and suggestions for research and applications”, *International Journal of Production Economics*, Vol. 154, pp. 72-80.

Hofer, C. W. (1975). “Toward a contingency theory of business strategy”, *Academy of Management Journal*, Vol. 18 No. 4, pp. 784–810.

Hu, M. and Liu, B. (2004). “Mining and summarizing customer reviews”. In *Proceedings of the tenth ACM SIGKDD international conference on knowledge discovery and data mining* (pp. 168-177). ACM.

Hulland, J., Baumgartner, H. and Smith, K. M. (2018). “Marketing survey research best practices: evidence and recommendations from a review of JAMS articles”, *Journal of the Academy of Marketing Science*, Vol. 46 No. 1, pp. 92-108.

Johnson, J.S., Friend, S.B. and Lee, H. S. (2017). “Big data facilitation, utilization, and monetization: Exploring the 3Vs in a new product development process”, *Journal of Product Innovation Management*, Vol. 34, No. 5, pp. 640-658.

Kaplan, D. (2000). Structural equation modeling: Foundation and extensions. Thousand Oaks, CA: Sage Publications.

Katsikeas, C. S., Morgan, N. A., Leonidou, L. C. and Hult, G. T. M. (2016). “Assessing performance outcomes in marketing”, *Journal of Marketing*, Vol. 80 No. 2, pp. 1-20.

Kitchens, B., Dobolyi, D., Li, J. and Abbasi, A. (2018). “Advanced customer analytics: Strategic value through integration of relationship-oriented big data”, *Journal of Management Information Systems*, Vol. 35 No. 2, pp. 540-574.

Lam, H. K., Yeung, A. C. and Cheng, T. E. (2016). “The impact of firms’ social media initiatives on operational efficiency and innovativeness”, *Journal of Operations Management*, Vol. 47, pp. 28-43.

Lam, H., Ding, L., Cheng, T. and Zhou, H. (2019). “The impact of 3D printing implementation on stock returns: A contingent dynamic capabilities perspective”, *International Journal of Operations & Production Management*, Vol. 39 No. 6/7/8, pp. 935-961.

Lee, G., Jeong, J., Seo, S., Kim, C. and Kang, P. (2018). “Sentiment classification with word localization based on weakly supervised learning with a convolutional neural network”, *Knowledge-Based Systems*, Vol. 152, pp. 70-82.

Lee, T. Y. and Bradlow, E. T. (2011). “Automated marketing research using online customer reviews”, *Journal of Marketing Research*, Vol. 48 No. 5, pp. 881-894.

Ling, L., Guo, X. and Yang, C. (2014). “Opening the online marketplace: An examination of hotel pricing and travel agency on-line distribution of rooms”, *Tourism Management*, Vol. 45, pp. 234-243.

Liu, J. and Toubia, O. (2018). “A semantic approach for estimating consumer content preferences from online search queries”, *Marketing Science*, Vol. 37 No. 6, pp. 930-952.

Liu, X., Shin, H. and Burns, A.C. (2019). “Examining the impact of luxury brands’ social media marketing on customer engagement: Using big data analytics and natural language processing", *Journal of Business Research*. *https://doi.org/10.1016/j.jbusres.2019.04.042*

Luo, X., Zhang, J. and Duan, W. (2013). "Social media and firm equity value", *Information Systems Research*, Vol. 24 No. 1, pp. 146-163.

McArthur, A. W. and Nystrom, P. C. (1991). "Environmental dynamism, complexity, and munificence as moderators of strategy-performance relationships", *Journal of Business Research*, Vol. 23 No.4, pp. 349–361.

Melville, N., Kraemer, K. and Gurbaxani, V. (2004). "Information technology and organizational performance: An integrative model of IT business value", *MIS Quarterly*, Vol. 28 No. 2, pp. 283-322.

Menicucci, E. (2018). "The influence of firm characteristics on profitability", *International Journal of Contemporary Hospitality Management*. Vol. 30 No. 8, pp. 2845-2868.

Mikalef, P., Boura, M., Lekakos, G. and Krogstie, J. (2019). "Big data analytics capabilities and innovation: the mediating role of dynamic capabilities and moderating effect of the environment", *British Journal of Management*, Vol. 30 No. 2, pp. 272–298.

Moe, W. W. and Schweidel, D. A. (2017). "Opportunities for innovation in social media analytics", *Journal of Product Innovation Management*, Vol. 34 No. 5, pp. 697-702.

Müller, O., Fay, M. and vom Brocke, J. (2018). "The effect of big data and analytics on firm performance: An econometric analysis considering industry characteristics", *Journal of Management Information Systems*, Vol. 35 No. 2, pp. 488-509.

Nam, H. and Kannan, P. K. (2014). "The informational value of social tagging networks", *Journal of Marketing*, Vol. 78 No. 4, pp. 21-40.

O'Rourke, N. and Hatcher, L. (2013). *A step-by-step approach to using SAS for factor analysis and structural equation modeling*. Cary:NC; Sas Institute.

Pansari, A. and Kumar, V. (2017). "Customer engagement: the construct, antecedents, and consequences", *Journal of the Academy of Marketing Science*, Vol. 45 No. 3, pp.294-311.

Park, Y., El Sawy, O.A. and Fiss, P. (2017). "The role of business intelligence and communication technologies in organizational agility: A configurational approach", *Journal of the Association for Information Systems*, Vol. 18 No. 9, pp. 648-686.

Pavlou, P.A. and El Sawy, O.A. (2010). "The 'third hand': IT-enabled competitive advantage in turbulence through improvisational capabilities", *Information Systems Research*, Vol. 21, No. 3, pp. 443-471.

PKF Consulting (1997). *Trends in the Hotel Industry*. Houston: Pannell, Kerr, and Forster.

Potter, A. and Paulraj, A. (2020). “Building supplier innovation triads: The effects of leadership relationships and alliance partner diversity”, *International Journal of Operations & Production Management*, Vol. 40 No. 2, pp. 144–172.

Proserpio, D. and Zervas, G. (2017). “Online reputation management: Estimating the impact of management responses on consumer reviews”, *Marketing Science*, Vol. 36 No. 5, pp. 645-665.

Radojevic, T., Stanisic, N. and Stanic, N. (2015). “Ensuring positive feedback: Factors that influence customer satisfaction in the contemporary hospitality industry”, *Tourism Management*, Vol. 51, pp. 13-21.

Raguseo, E., Neirotti, P. and Paolucci, E. (2017). “How small hotels can drive value their way in infomediation. The case of ‘Italian hotels vs. OTAs and TripAdvisor”, *Information & Management*, Vol. 54 No. 6, pp. 745-756.

Ramanathan, U., Subramanian, N. and Parrott, G. (2017). “Role of social media in retail network operations and marketing to enhance customer satisfaction”, *International Journal of Operations & Production Management*, Vol. 37 No. 1, pp. 105-123.

Read, M. (2018). How much of the internet is fake? Turns out, a lot of it, actually. Available at: http://nymag.com/intelligencer/2018/12/how-much-of-the-internet-is-fake.html.

Roh, J., Krause, R. and Swink, M. (2016). “The appointment of chief supply chain officers to top management teams: A contingency model of firm-level antecedents and consequences”, *Journal of Operations Management*, Vol. 44, pp. 48-61.

Ross, J. W., Beath, C. M. and Quaadgras, A. (2013). “You may not need big data after all”, *Harvard Business Review*, Vol. 91, No. 12, pp. 90.

Saboo, A. R., Kumar, V. and Anand, A. (2017). “Assessing the impact of customer concentration on initial public offering and balance sheet-based outcomes”, *Journal of Marketing*, Vol. 81 No. 6, pp. 42-61.

Sardeshmukh, S. R., & Vandenberg, R. J. (2017). “Integrating moderation and mediation: A structural equation modeling approach”, *Organizational Research Methods*, Vol. 20 No. 4, pp. 721–745.

Sawhney, M., Verona, G. and Prandelli, E. (2005). “Collaborating to create: The Internet as a platform for customer engagement in product innovation”, *Journal of Interactive Marketing*, Vol. 19 No. 4, pp.4-17.

Schivinski, B., Christodoulides, G. and Dabrowski, D. (2016). “Measuring consumers' engagement with brand-related social-media content: Development and validation of a scale that identifies levels of social-media engagement with brands”, *Journal of*

Advertising Research, Vol. 56 No. 1, pp.64-80.

Shu, E. and Lewin, A.Y. (2017). "A resource dependence perspective on low-power actors shaping their regulatory environment: The case of Honda", *Organization Studies*, Vol. 38 No. 8, pp. 1039-1058.

Simon, F. and Tossan, V. (2018). "Does brand-consumer social sharing matter? A relational framework of customer engagement to brand-hosted social media", *Journal of Business Research*, Vol. 85, pp.175-184.

Sousa, R. and Voss, C. A. (2008). "Contingency research in operations management practices", *Journal of Operations Management*, Vol. 26 No. 6, pp. 697-713.

Srinivasan, R. and Swink, M. (2018). "An investigation of visibility and flexibility as complements to supply chain analytics: An organizational information processing theory perspective", *Production and Operations Management*, Vol. 27 No. 10, pp. 1849-1867.

Steven, A. B., Dong, Y. and Corsi, T. (2014). "Global sourcing and quality recalls: An empirical study of outsourcing-supplier concentration-product recalls linkages", *Journal of Operations Management*, Vol. 32 No. 5, pp. 241-253.

Taboada, M., Brooke, J., Tofiloski, M., Voll, K. and Stede, M. (2011). "Lexicon-based methods for sentiment analysis", *Computational Linguistics*, Vol. 37 No. 2, pp. 267-307.

Terjesen, S., Patel, P.C. and Covin, J.G. (2011). "Alliance diversity, environmental context and the value of manufacturing capabilities among new high technology ventures", *Journal of Operations Management*, Vol. 29 No. 1–2, pp. 105–115.

Thao, V. T., von Arx, W. and Frölicher, J. (2019). "Swiss Cooperation in the Travel and Tourism Sector: Long-term Relationships and Superior Performance', *Journal of Travel Research*. https://doi.org/10.1177/0047287519871105.

Toubia, O., Iyengar, G., Bunnell, R. and Lemaire, A. (2019). "Extracting Features of Entertainment Products: A Guided Latent Dirichlet Allocation Approach Informed by the Psychology of Media Consumption", *Journal of Marketing Research*, Vol. 56 No. 1, pp. 18-36.

Tse, Y.K., Loh, H., Ding, J. and Zhang, M. (2018). "An investigation of social media data during a product recall scandal", *Enterprise Information Systems*, Vol. 12 No. 6, pp. 733-751.

Van Beers, C. and Zand, F. (2014). "R&D cooperation, partner diversity, and innovation performance: an empirical analysis", *Journal of Product Innovation Management*, Vol. 31 No. 2, pp. 292–312.

Wang, Y. and Byrd, T. A. (2017). “Business analytics-enabled decision-making effectiveness through knowledge absorptive capacity in health care”, *Journal of Knowledge Management*, Vol. 21 No. 3, pp. 517-539.

Wang, Y., Kung, L. and Byrd, T. A. (2018). “Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations”, *Technological Forecasting and Social Change*, Vol. 126, pp. 3-13.

Wang, Y., Kung, L., Gupta, S. and Ozdemir, S. (2019). “Leveraging big data analytics to improve quality of care in healthcare organizations: A configurational perspective”, *British Journal of Management*, Vol. 30 No. 2, pp. 362-388.

Wong, C. Y., Boon-Itt, S. and Wong, C. W. (2011). “The contingency effects of environmental uncertainty on the relationship between supply chain integration and operational performance”, *Journal of Operations Management*, Vol. 29 No. 6, pp. 604-615.

Xiang, Z., Du, Q., Ma, Y. and Fan, W. (2017). “A comparative analysis of major online review platforms: Implications for social media analytics in hospitality and tourism”, *Tourism Management*, Vol. 58, pp. 51-65.

Xue, L., Ray, G. and Sambamurthy, V. (2012). “Efficiency or innovation: How do industry environments moderate the effects of firms' IT asset portfolios?”, *MIS Quarterly*, Vol. 36 No. 2, pp. 509-528.

Ye, F., Zhang, L. and Li, Y. (2018). “Strategic choice of sales channel and business model for the hotel supply chain”, *Journal of Retailing*, Vol. 94 No. 1, pp. 33-44.

Zhao, Y., Xu, X. and Wang, M. (2019). Predicting overall customer satisfaction: Big data evidence from hotel online textual reviews. *International Journal of Hospitality Management*, Vol. 76, pp. 111-121.

Zhu, K. and Kraemer, K.L. (2005). “Post-adoption variations in usage and value of e-business by organizations: Cross-country evidence from the retail industry”, *Information Systems Research*, Vol. 16 No. 1, pp. 61–84.

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