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THE CONFIGURATIONAL IMPACT OF TOP MANAGEMENT TEAM CHARACTERISTICS ON MARKETING ANALYTICS USE IN SME: A FUZZY-SET QUALITATIVE COMPARATIVE ANALYSIS

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Abstract
Top management team might make primary usage decisions related to marketing analytics. To date, extant research has mostly focused on investigating the impact of marketing analytics on firm performance; limited research exists to examine the conditions of utilizing marketing analytics. Furthermore, little is known about how the combinations of conditions affect marketing analytics use. Drawing on upper echelons and configuration theories, this study proposes that small and medium-sized enterprises (SMEs) have alternative pathways to utilizing marketing analytics. Based on a sample of 187 managers from UK SMEs and employing fuzzy set qualitative comparative analysis (fsQCA), this study confirms that (1) configurations of antecedents exist to provide alternative pathways to utilizing marketing analytics, and (2) configurations for small firms are distinctively different from those for medium-sized firms. This study contributes to upper echelon theory and configuration theory by highlighting different pathways to marketing analytics use. This study also helps a firm to improve its analytics practice by choosing the configuration that fits best with its organizational context.

Keywords: marketing analytics, antecedents, configurations, upper echelons, top management team, small to medium-sized enterprises, fsQCA

1. Introduction
Marketing analytics, a domain of business analytics (Holsapple *et al.* 2014), has become an essential and desirable tool for the success of firms and extant research indicated that firms can use marketing analytics to support decision-making and to stay competitive (e.g., Germann *et al.* 2013; Wedel and Kannan 2016). Despite the potential benefits from utilizing marketing analytics, evidence suggests that not many firms are currently using marketing analytics (Ariker et al. 2015; Wedel and Kannan 2016), with challenges attributed to the lack of substantial resources to exploit analytics, particularly evident for small and medium-sized enterprises (SMEs) (Gillon et al. 2014). Motivated by this debate, this study aims to examine the determinants of utilizing marketing analytics within SMEs, which account for around 99% of all UK enterprises and are considered to be the backbone of UK economy (Blackwell *et al.* 2006). While existing research has mostly focused on examining the performance impact of marketing analytics, there is limited research on the conditions of utilizing marketing analytics. Two key gaps can be identified in the context of exploiting marketing analytics.

First, research suggests that understanding the conditions required for utilizing business analytics remains an important gap in the literature (Trieu 2017). Whilst some prior studies suggest that the use of business analytics or marketing analytics can be affected by several antecedents (e.g., Germann *et al.* 2013; Chen *et al.* 2015; Gupta and George 2016), however, little research exists to generally examine how top management team's characteristics influence analytics use, albeit an organization is the reflection of its top managers' values and cognitive bases (Hambrick and Mason 1984; Hambrick 2007). It follows, then, there is a need to develop a deeper understanding of how top managers' characteristics affect marketing analytics use.

Second, little research exists to investigate the configurations of causal conditions of utilizing marketing analytics. Prior studies have typically employed regression-based methods to examine the cause-effect relationships between analytics use and its antecedents (e.g., Germann *et al.* 2013; Chen *et al.* 2015; Wedel and Kannan 2016; Gunasekaran *et al.* 2017). However, such analysis ignores the complex interdependencies between variables. A configuration on the other hand refers to a specific combination of causal variables that generates an outcome of interest (Fiss 2007, 2011). Configurational approach suggests that an outcome of interest seldom has a single cause but is best explained through multi-causality considerations. In other words, "the recipe is more important than the ingredients" (Ordanini *et al.* 2014).

Drawing on upper echelon and configuration theories, this study posits that SMEs could have alternative pathways, that is, combinations of conditions that lead to marketing analytics use. Thus, the goal of this study is to investigate whether or not the use of marketing analytics can be explained by the configurations of antecedents holistically, rather than through any single antecedent. Specifically, two key research questions are to be addressed: what are the configurations that lead to marketing analytics use, and what are the configuration similarities and differences, if any, between small and medium-sized firms?

2. Theoretical considerations

2.1. Marketing analytics use

Marketing analytics use in this study refers to the extent to which a firm is employing marketing analytics to support marketing decision making (Ariker *et al.* 2015; CMO-Survey 2015, 2016). Although marketing analytics use is seen to enable firms to improve decision-making and performance, the actual use, however, is surprisingly limited (Ariker et al. 2015; Wedel and Kannan 2016). Thus, it is vital to understand the conditions of utilizing marketing analytics so that firms could benefit from utilizing marketing analytics.

Prior studies have mostly focused on examining the performance effects of marketing analytics use; general research on the conditions of utilizing marketing analytics has not attracted as much attention. However, an organization is the reflection of its top managers (Hambrick and Mason 1984; Hambrick 2007) and they might make primary adoption decisions related to IT (Lewis *et al.* 2003). Therefore, it would be useful to develop an understanding of how top managers' characteristics in SMEs may influence marketing analytics use.

2.2. Top management team's characteristics

According to upper echelons theory, a firm's top managers' characteristics may greatly influence their interpretations of the situations they face and in turn their strategic choices (Hambrick and Mason 1984; Hambrick 2007). It follows then that SMEs would benefit from a deeper understanding of how top managers' characteristics and their interpretations affect marketing analytics use. Specifically, this study will look at managerial perception and support, competitive pressure, data availability, and organizational readiness, which have been identified by prior analytics studies (e.g., Germann *et al.* 2013; Chen *et al.* 2015; Gupta and George 2016).

First, managerial perception in IT studies generally refers to the degree to which top management team views IT as critical to an organization's success (Liang *et al.* 2007), which is the primary determinant of IT adoption (Thong 1999; Oliveira *et al.* 2014). In line with these, top managers' positive perception of employing marketing analytics is expected to lead to the actual use of marketing analytics.

Second, managerial support refers to the extent to which top management team understands, appreciates, and promotes the use of marketing analytics (Germann *et al.* 2013). Recently, analytics studies demonstrate that managerial support is positively associated with big data analytics use (Chen *et al.* 2015), and necessary for the effective deployment of marketing analytics (Germann *et al.* 2013).

Third, data availability refers to the extent of a firm's access to data for analysis, data integration of multiple internal sources for easy access, and integration of external and internal data (Gupta and George 2016). It is anticipated that a firm's top managers would ensure that data is available when they view data as a core strategic asset that enables the firm to make successful decisions and to differentiate its products (Erevelles *et al.* 2016).

Forth, competitive pressure is understood in terms of the extent to which a firm's competitors, suppliers and customers have employed IT, which may apply some coercive pressure on a firm's top managers to use similar IT (Liang et al. 2007). Similarly, this study expects that competitive pressure will affect how top managers interpret the analytics situations they face and in turn their decisions about utilizing marketing analytics.

Fifth, organizational readiness refers to the extent to which organizational resources are available for using marketing analytics, in line with prior studies (Iacovou *et al.* 1995; Chen *et al.* 2015). Chen *et al.* (2015), in the context of big data analytics, suggest that a firm's top management will be more supportive when they believe that the firm has sufficient resources in place to promote big data analytics use.

2.3. Firm size matters

Prior studies suggest that firm size matters and tends to be associated with different patterns of IT investment and use (Thong *et al.* 1996; Thong 1999; Gillon *et al.* 2014). SMEs are normally seen as one homogeneous group to be differentiated from large firms; research has not yet produced conclusive evidence about the differences between small firms and medium-sized enterprises. However, there is evidence in the literature to suggest that small and medium-sized firms have differences (Laukkanen *et al.* 2007; Neirotti *et al.* 2013). Accordingly, it is possible that small and medium-sized firms could differ in terms of marketing analytics use.

2.4. A configurational approach

Acording to Dess *et al.* (1993), "a configuration represents a number of specific and separate attributes which are meaningful collectively rather than individually". Thus, a configurational approach suggests that an outcome of interest seldom has a single cause but is best explained through multi-causality considerations; and that causes are interdependent rather than operating in isolation from each other. Fundamentally, configuration theory accomodates the principle of equifinality–that is, "a system can reach the same final state from different initial conditions and by a variety of different paths of development" (Katz and Kahn 1978, p.30). Lately, fuzzy-set qualitative comparative analysis (fsQCA) has gained increasing attention and application in organizational research, which is seen to be uniquely suitable for dealing with configurations (Fiss 2007; Ragin 2008; Fiss 2011; Woodside 2013).

3. Research method

3.1. Sample

The FAME database (Financial Analysis Made Easy) was utilized to obtain a convenience sample of 32,118 senior and middle managers of UK firms. A survey questionnaire was developed and then distributed to managers electronically through Qualtrics, an online survey tool. Of all sent emails, 187 usable responses were received, 104 responses from small firms with less than 50 employees and 83 responses from firms with more than 50 but less than 250 employees.

Since data was gathered from a single key respondent within each firm, a potential for common method bias exists. To address this issue, first, a procedural remedy was used to improve scale items through defining them clearly. In addition, positively and negatively worded measures were also used to control for acquiescence and disacquiescence biases (Podsakoff *et al.* 2012). Secondly, the Harman single-factor test was conducted and the first factor accounting for 13.81% of the total variance, suggesting that common method bias was not a serious concern. Non-response bias was also tested to ensure that the sample was representative of the panel population. A t-test was conducted, which showed that both groups did not differ significantly in their responses, indicating no systematic differences between early and late respondents.

3.2. Measurement

In line with previous analytics research, the outcome variable– marketing analytics use was measured using Likert scales, ranging from 1 = no use to 7 = very heavy use. Three different types were differentiated based on 13 items reported by CMO-Surveys (2015, 2016): (1) customer-oriented use of marketing analytics in the areas of customer insight, customer acquisition, customer retention, and segmentation; (2) product-oriented use of marketing analytics in the areas of new product or service development, product or service strategy, promotion strategy, pricing strategy, marketing mix, and branding; and (3) general marketing-oriented use of marketing analytics in relation to digital marketing, social media, and multichannel marketing. As regards the five antecedents examined, they were measured using Likert scales (1 = strongly disagree to 7 = strongly agree). Data availability was measured using three items adopted from Gupta and George (2016). Managerial perception was measured using four items adapted from prior studies (Kearns and Sabherwal 2007; Liang *et al.* 2007). Managerial support was measured based on three items adapted from prior studies (Liang *et al.* 2007; Germann *et al.* 2013; Chen *et al.* 2015). Competitive pressure was measured using three items adapted from Liang *et al.* (2007). Finally, organizational readiness was measured using four items adapted from prior studies (Iacovou *et al.* 1995; Chen *et al.* 2015). The construct validity of the measurement was assessed in terms of the internal consistency (composite reliability (CR)), indictor reliability, convergent validity and discriminant validity (Table 1). The values of CR and average variance extracted (AVE) for the constructs are all above the thresholds 0.7 and 0.5 respectively; thus they are adequate.

Table 1. Measurement items and descriptive statistics

Constructs	Indicators (1- strongly disagree to 7-strongly agree)	Mean (SD)	CR	AVE

Competitive pressure (Liang *et al.* 2007)	Our competitors have implemented marketing analytics to collect, manage, and analyze data to extract useful insights	4.39 (1.45)	0.84	0.64
	Our suppliers have implemented marketing analytics to collect, manage, and analyze data to extract useful insights	4.24 (1.56)		
	Our customers have implemented marketing analytics to collect, manage, and analyze data to extract useful insights	4.02 (1.58)		
Data Availability (Gupta and George 2016)	We have access to very large, unstructured, or fast-moving data for analysis	4.01 (1.68)	0.84	0.64
	We integrate data from multiple internal sources into a data warehouse or mart for easy access	3.62 (1.84)		
	We integrate external data with internal to facilitate high-value analysis of our business environment	3.59 (1.75)		
Managerial perception (Kearns and Sabherwal 2007)	Top management team recognizes the strategic potential of marketing analytics	5.11 (1.48)	0.89	0.68
	Top management team is knowledgeable about marketing analytics opportunities	4.45 (1.52)		
	Top management team is familiar with competitor's strategic use of marketing analytics	3.85 (1.48)		
	Top management team believes marketing analytics contributes significantly to firm performance	4.26 (1.54)		
Managerial support (Liang *et al.* 2007; Germann *et al.* 2013; Chen *et al.* 2015)	Top management team promotes the use of marketing analytics in your company	4.00 (1.66)	0.97	0.91
	Top management team creates support for marketing analytics initiatives within your company	4.07 (1.65)		
	Top management team has promoted marketing analytics as a strategic priority within your company	3.73 (1.68)		
Organizational readiness (Iacovou *et al.* 1995; Chen *et al.* 2015)	We have the capital/financial resources to fully exploit marketing analytics	4.01 (1.76)	0.89	0.68
	We have the needed IT infrastructure to fully exploit marketing analytics	4.19 (1.69)		
	We have the analytics capability to fully exploit marketing analytics	3.83 (1.73)		
	We have the skilled resources to fully exploit marketing analytics	3.71 (1.70)		
Customer-related* (Ariker *et al.* 2015; CMO-Survey 2015, 2016)	We implemented marketing analytics in customer insight	3.49 (1.52)	0.92	0.74
	We implemented marketing analytics in customer acquisition	3.25 (1.59)		
	We implemented marketing analytics in customer retention	3.39 (1.56)		
	We implemented marketing analytics in customer segmentation	3.08 (1.60)		
Product-related* (Ariker *et al.* 2015; CMO-Survey 2015, 2016)	We implemented marketing analytics in new product or service development	3.46 (1.66)	0.94	0.73
	We implemented marketing analytics in product or service strategy	3.28 (1.58)		
	We implemented marketing analytics in promotion strategy	3.47 (1.66)		
	We implemented marketing analytics in pricing strategy	3.34 (1.60)		
	We implemented marketing analytics in marketing mix	3.25 (1.66)		
	We implemented marketing analytics in branding	3.26 (1.63)		
Marketing-related* (Ariker *et al.* 2015; CMO-Survey 2015, 2016)	We implemented marketing analytics in digital marketing	3.63 (1.67)	0.93	0.81
	We implemented marketing analytics in social media	3.55 (1.70)		
	We implemented marketing analytics in multichannel marketing	2.92 (1.64)		

*-measured based on a seven-point Likert scale ranging from no use, very low use, low use, moderate use, somewhat heavy use, quite heavy use, to very heavy use

3.3. Calibration

fsQCA 3.0 program (Ragin and Davey 2016) was used. Based on the calibration procedure introduced by Ragin (2008), survey data was transformed into fuzzy sets with values ranging from 0–no set membership to 1–full set membership. Since this study uses a seven-point Likert scale to quantify constructs, in line with the guideline of calibration for survey measurement (Fiss 2011; Ordanini *et al.* 2014; Park *et al.* 2017), this study defined a value of 6 as the full membership anchor, 2 as the anchor for full non-membership, and 4 as the crossover point.

4. Analysis

4.1. Analysis of sufficient conditions

In fsQCA, a causal condition is defined as sufficient if by itself it can produce a certain outcome (Fiss 2011; Zaefarian *et al.* 2017). Next, the data will be analyzed to identify which combinations of conditions are sufficient to obtain the outcome. This starts with the construction of a truth table, listing all logically possible configurations of the conditions for an outcome. As five antecedents were considered, the truth table consists of $2^5 = 32$ different configurations. To reduce the truth table to meaningful configurations, a frequency threshold of four observations is chosen to exclude less important configurations.

In order to define which configurations are sufficient for achieving the outcome, this study sets consistency for solutions at ≥ 0.77, which is above the minimum threshold of 0.75 recommended by Ragin (2008) and Woodside (2013). The fsQCA software produces complex, intermediate and parsimonious solutions. In general, the number of complex solutions can be large and often include impractical configurations (Liu *et al.* 2017). For this reason, they are usually simplified further into parsimonious and intermediate solutions that allow core or peripheral conditions to be differentiated, with "core elements as those causal conditions for which the evidence indicates a strong causal relationship with the outcome of interest and peripheral elements as those for which the evidence for a causal relationship with the outcome is weaker" (Fiss 2011, p.394). In fsQCA, core conditions are those that are part of both parsimonious and intermediate solutions, peripheral conditions are those that only appear in the intermediate solution.

Table 2 summarizes the intermediate solutions with the presence of use of customer-, marketing-, and product-oriented analytics as outcomes. Black circles "●" represent the presence of causal conditions and white circles "○" represent the absence or negation of causal conditions. The blank cells represent "doesn't matter" conditions. Furthermore, "large circles indicate core conditions, and small circles refer to peripheral conditions"(Fiss 2011).

To conclude whether or not the configurations are informative, two measures are available: consistency and coverage. First, consistency measures the extent to which a configuration corresponds to the outcome. As all of the consistency scores exceed the cut-off value (≥ 0.75), all configurations can be considered as sufficient for the outcome (Fiss 2007, 2011). Second, the coverage scores assess the proportion of cases that follow a particular path and thus capture the empirical importance of an identified configuration. The raw coverage quantifies the proportion of outcome cases explained by a given configuration. The higher the raw coverage, the larger the proportion of the high use of marketing analytics can be explained by the given configuration, ranging from 0.32 to 0.55. Unique coverage measures the proportion of outcome cases that are uniquely covered by a given path (Ragin 2008), which should be larger than zero; otherwise the configuration does not contribute to the explanation of the outcome (Zaefarian et al. 2017). Table 2 indicates that this requirement is fulfilled.

Table 2. Configurations for marketing analytics use in small and medium-sized firms

Configuration	Customer-oriented			Marketing-oriented		Product-oriented		
	Small	Medium-sized a	Medium-sized b	Small	Medium-sized	Small	Medium-sized a	Medium-sized b
Competitive pressure	•	•	○	•	•	•		•
Data availability	●		●	●	●	●	●	
Managerial perception	•	•	•	•	•	•	•	•
Managerial support	•	●	•	•	•	•	•	●
Organizational readiness	●	●	○	●	●	●	○	●
Raw coverage	0.50	0.55	0.32	0.48	0.49	0.47	0.44	0.54
Unique coverage	0.50	0.31	0.07	0.48	0.49	0.47	0.15	0.24
Solution consistency	0.77	0.80	0.81	0.79	0.83	0.76	0.76	0.81
Solution coverage	**0.50**	**0.62**		**0.48**	**0.49**	**0.47**	**0.68**	
Solution consistency	**0.77**	**0.78**		**0.79**	**0.83**	**0.76**	**0.76**	

Note. ● = core causal condition present; • = peripheral causal condition present; ○ = peripheral causal condition absent

Finally, the solution coverage of the overall model refers to the joint importance of all configurations. For example in small firms, the overall solution coverage accounted for 0.50 for customer-oriented analytics use, 0.48 for marketing-oriented and 0.47 for product-oriented. Thus, they are seen to be informative.

4.2. Configurations for the presence of marketing analytics use

Overall, the solution in Table 2 shows that the configurations differ by firm size. For small firms, there is only one configuration for marketing analytics use across customer-, marketing-, and product-oriented areas. However, multiple configurations exist for marketing analytics use in medium-sized firms. With respect to customer- and product-oriented areas, there are two configurations leading to analytics use. However, there is only one configuration leading to the use of marketing-oriented analytics.

The results also indicate the presence of different patterns of core and peripheral conditions of utilizing marketing analytics. Specifically, for small firms, the combination of data availability and organizational readiness is core and all other antecedents are peripheral conditions. For medium-sized firms, the combination of managerial support and organizational readiness is core for utilizing customer- (configuration a) and product-oriented (configuration b) analytics, and data availability is core for utilizing customer- (configuration b) and product-oriented (configuration a) analytics; and the combination of data availability and organizational readiness is core for utilizing marketing-oriented analytics.

5. Discussion and implications

5.1. Theoretical discussion and implications

Prior studies have examined discrete antecedents to business or marketing analytics use (e.g., Germann *et al.* 2013; Chen *et al.* 2015; Wedel and Kannan 2016; Gunasekaran *et al.* 2017). These studies usually suggest that firms tend to use business or marketing analytics to improve decision-making and organizational performance when certain antecedents or conditions are present or satisfied. Given that an organization is the reflection of its top managers (Hambrick and Mason 1984; Hambrick 2007), it is anticipated that a firm's top management team characteristics may significantly influence marketing analytics use. Yet, such research is lacking. Drawing on upper echelons theory (Hambrick and Mason 1984; Hambrick 2007), this study empirically examined five conditions of utilizing marketing analytics and confirmed that a firm's use of marketing analytics is greatly influenced collectively by its top managers' perception of the importance of marketing analytics, their interpretations of the pressure from business partners and customers to utilize marketing analytics, their support for the use of marketing analytics, data being integrated and available, and that the firm being ready to use marketing analytics. This study provides additional empirical evidence to support the need and significance of examining the determinants of IT use in organizations (Lewis *et al.* 2003; Oliveira *et al.* 2014; Veiga *et al.* 2014) in the context of marketing analytics. Additionally, it confirms and complements prior analytics studies to the degree that antecedents indeed play an important role in influencing marketing analytics use (e.g., Germann *et al.* 2013; Chen *et al.* 2015; Wedel and Kannan 2016; Gunasekaran *et al.* 2017).

More importantly, this study has further extended the scope of research on the relationship between antecedents and marketing analytics use based on a configurational approach. Prior analytics studies typically investigate the net effects of individual antecedents on the use of marketing analytics. However, there is a lack of research considering the interdependencies among multiple antecedents. Configuration theory points to the importance and the possibility of understanding which factors are relevant to achieving a desired outcome and what combinations of these factors will lead to that outcome (Fiss 2007, 2011). Drawing on configuration theory and employing fsQCA, this study is among the first empirical studies applying configuration theory to investigating marketing analytics use. This study simultaneously analyzes key antecedents of utilizing marketing analytics and shows how combinations of antecedents jointly influence marketing analytics use. Specifically, this study looks at different configurations of antecedents and their effects on utilizing marketing analytics in SMEs. The results provide evidence that there are multiple configurations for utilizing marketing analytics, shaped by the combinations of multiple antecedents rather than by individual conditions.

Specifically, the findings show that for medium-sized firms, data availability is a core condition for most configurations for the use of marketing analytics. The combination of organizational readiness with either managerial support or data availability is another core condition for most configurations of marketing analytics use. This is consistent with the idea that lacking necessary resources is a significant issue for IT adoption in SMEs (e.g., Thong *et al.* 1996).

Finally, this study's finding provides new insights into how small firms use marketing analytics. This study suggests that there is only one sufficient configuration leading to marketing analytics use, which is shaped collectively by five conditions with data availability and organizational readiness as two core conditions. This suggests that for those small firms wishing to employ marketing analytics successful, a more holistic approach is necessary to make sure that all key conditions are satisfied.

5.2. Managerial implications

This study offers several implications for managerial practice. Firstly, firms should be aware of the fact that marketing analytics use is influenced holistically by the interaction of conditions. This implies that unless all conditions are satisfied, SMEs will most likely fail in their efforts to implement marketing analytics. In order for firms to use marketing analytics effectively to support decision-making and to stay competitive, they need to consider organizational conditions as a whole.

Secondly, multiple configurations exist for marketing analytics use in medium-sized firms; hence a medium-sized firm should choose the configuration that fits best with its organizational context. However, for small firms, this study suggests that there is only one sufficient configuration for utilizing marketing analytics: they need to holistically satisfy several conditions simultaneously. Top management team must be aware of and responding to competitive pressure from suppliers, customers and competitors, with positive perception of the strategic value of, and support for, marketing analytics use, and ensure that resources are in place for the use of marketing analytics.

Thirdly, data availability and organizational readiness are two core conditions for almost all configurations leading to marketing analytics use. Thus, a firm's top management team needs to make sure that resources are directed to meeting the two core conditions, without which the firm would not be able to utilize marketing analytics effectively.

5.3. Limitations and future research

There are several limitations in this study, which offer opportunities for future research. First, the study includes five antecedents that jointly influence the use of marketing analytics. The identified antecedents focused on top management team's characteristics and might not cover the full range of conditions affecting the use of marketing analytics. Therefore, one potential avenue for future research is to extend this study by adding additional antecedents or different set of conditions, thereby to either test the usefulness of the configurations identified in this study or identify new configurations

Secondly, this study's sample restricted to small and medium-sized firms in the U.K. Thus the findings should be understood in this context and its applicability to other countries needs to be tested. Future research could be conducted to investigate whether or not the configurations identified in this study are likely to differ in different research contexts.

Finally, this study used a single key-informant method to collect subjective data from each firm. Although this study followed relevant procedure and conducted the Harman single-factor test to make sure that common method bias was not a main concern, future research could collect objective data if it is available and/or use multiple informants from each firm to limit potential subjective bias.

5.4. Conclusions

This study suggests that configurations of antecedents are likely to offer a holistic understanding of how the combination of conditions leading to marketing analytic use. While marketing analytics use can be influenced by individual antecedents such as top management support, ultimately it is the configuration of various conditions that determines the success or failure of the implementation. The implication for SMEs is that in order to utilize marketing analytics effectively to support decision-making, they should focus on selecting the configuration that best fits their own organizational context. The implication for research is that a configurational approach is suitable for examining configurations that allow holistic understanding of analytics phenomenon to be developed.

References

Ariker, M., Diaz, A., Moorman, C., & Westover, M. (2015). Quantifying the Impact of Marketing Analytics. *Harvard Business Review Digital Articles*, 2-5.

Blackwell, P., Shehab, E. M., & Kay, J. M. (2006). An effective decision-support framework for implementing enterprise information systems within SMEs. *International Journal of Production Research, 44*(17), 3533-3552.

Chen, D., Preston, D. S., & Swink, M. (2015). How the Use of Big Data Analytics Affects Value Creation in Supply Chain Management. *Journal of management information systems*, *32*(4), 4-39.
CMO-Survey. (2015). Highlights and Insights Report. Retrieved April 28, 2017, from https://cmosurvey.org/wp-content/uploads/sites/11/2015/09/The_CMO_Survey-Highlights_and_Insights-Aug-2015.pdf
CMO-Survey. (2016). Highlights and Insights Report. Retrieved April 28, 2017, from https://cmosurvey.org/wp-content/uploads/sites/11/2016/08/The_CMO_Survey-Highlights_and_Insights-Aug-2016.pdf
Dess, G. G., Newport, S., & Rasheed, A. M. (1993). Configuration research in strategic management: Key issues and suggestions. *Journal of Management*, *19*(4), 775-795.
Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big Data consumer analytics and the transformation of marketing. *Journal of Business Research, 69*(2), 897-904.
Fiss, P. C. (2007). A set-theoretic approach to organizational configurations. *Academy of management review*, *32*(4), 1180-1198.
Fiss, P. C. (2011). Building better casual theories: A fuzzy set approach to typologies in organizational research. *Academy of Management Journal, 54*(2), 393-420.
Germann, F., Lilien, G. L., & Rangaswamy, A. (2013). Performance implications of deploying marketing analytics. *International Journal of Research in Marketing*, *30*(2), 114-128.
Gillon, K., Aral, S., Ching-Yung, L., Mithas, S., & Zozulia, M. (2014). Business analytics: radical shift or incremental change? *Communications of the Association for Information Systems, 34*(1), 287-296.
Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., Childe, S. J., Hazen, B., & Akter, S. (2017). Big data and predictive analytics for supply chain and organizational performance. *Journal of Business Research, 70*(Supplement C), 308-317.
Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability. *Information & Management*, *53*(6), 1049-1064.
Hambrick, D. C. (2007). Upper echelons theory: An update. *Academy of management review, 32*(2), 334-343.
Hambrick, D. C., & Mason, P. A. (1984). Upper echelons: The organization as a reflection of its top managers. *Academy of management review*, *9*(2), 193-206.
Holsapple, C., Lee-Post, A., & Pakath, R. (2014). A unified foundation for business analytics. *Decision Support Systems*, *64*, 130-141.
Iacovou, C. L., Benbasat, I., & Dexter, A. S. (1995). Electronic data interchange and small organizations: Adoption and impact of technology. *MIS Quarterly*, *19*(4), 465-485.
Katz, D., & Kahn, R. L. (1978). *The social psychology of organizations* (Vol. 2): Wiley New York.
Kearns, G. S., & Sabherwal, R. (2007). Antecedents and consequences of information systems planning integration. *IEEE Transactions on Engineering Management*, *54*(4), 628-643.
Laukkanen, S., Sarpola, S., & Hallikainen, P. (2007). Enterprise size matters: objectives and constraints of ERP adoption. *Journal of Enterprise Information Management, 20*(3), 319-334.
Lewis, W., Agarwal, R., & Sambamurthy, V. (2003). Sources of influence on beliefs about information technology use: An empirical study of knowledge workers. *MIS Quarterly, 27*(4), 657-678.
Liang, H., Saraf, N., Hu, Q., & Xue, Y. (2007). Assimilation of enterprise systems: the effect of institutional pressures and the mediating role of top management. *MIS Quarterly*, 59-87.

Liu, Y., Mezei, J., Kostakos, V., & Li, H. (2017). Applying configurational analysis to IS behavioural research: a methodological alternative for modelling combinatorial complexities. *Information Systems Journal, 27*(1), 59-89.
Neirotti, P., Paolucci, E., & Raguseo, E. (2013). Is it all about size? Comparing organisational and environmental antecedents of IT assimilation in small and medium-sized enterprises. *International Journal of Technology Management, 61*(1), 82-108.
Oliveira, T., Thomas, M., & Espadanal, M. (2014). Assessing the determinants of cloud computing adoption: An analysis of the manufacturing and services sectors. *Information & Management, 51*(5), 497-510.
Ordanini, A., Parasuraman, A., & Rubera, G. (2014). When the recipe is more important than the ingredients: A qualitative comparative analysis (QCA) of service innovation configurations. *Journal of Service Research, 17*(2), 134-149.
Park, Y., El Sawy, O. A., & Fiss, P. C. (2017). The Role of Business Intelligence and Communication Technologies in Organizational Agility: A Configurational Approach. *Journal of the Association for Information Systems, 18*(9), 648-686.
Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of Method Bias in Social Science Research and Recommendations on How to Control It. *Annual Review of Psychology, 63*(1), 539-569.
Ragin, C. C. (2008). *Redesigning social inquiry: Fuzzy sets and beyond*: University of Chicago Press.
Ragin, C. C., & Davey, S. (2016). *Fuzzy-Set/Qualitative Comparative Analysis 3.0.* . Irvine, California: Department of Sociology, University of California.
Thong, J. Y. L. (1999). An integrated model of information systems adoption in small businesses. *Journal of management information systems, 15*(4), 187-214.
Thong, J. Y. L., Chee-Sing, Y., & Raman, K. S. (1996). Top Management Support, External Expertise and Information Systems Implementation in Small Businesses. *Information Systems Research, 7*(2), 248-267.
Trieu, V.-H. (2017). Getting value from Business Intelligence systems: A review and research agenda. *Decision Support Systems, 93*, 111-124.
Veiga, J. F., Keupp, M. M., Floyd, S. W., & Kellermanns, F. W. (2014). The longitudinal impact of enterprise system users' pre-adoption expectations and organizational support on post-adoption proficient usage. *European Journal of Information Systems, 23*(6), 691-707.
Wedel, M., & Kannan, P. K. (2016). Marketing Analytics for Data-Rich Environments. *Journal of Marketing, 80*(6), 97-121.
Woodside, A. G. (2013). Moving beyond multiple regression analysis to algorithms: Calling for adoption of a paradigm shift from symmetric to asymmetric thinking in data analysis and crafting theory. *Journal of Business Research, 66*, 463-472.
Zaefarian, G., Thiesbrummel, C., Henneberg, S. C., & Naudé, P. (2017). Different recipes for success in business relationships. *Industrial Marketing Management, 63*(Supplement C), 69-81.