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A dynamic capability view of marketing analytics: Evidence from UK firms

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ABSTRACT

While marketing analytics plays an important role in generating insights from big data to improve marketing decision-making and firm competitiveness, few academic studies have investigated the mechanisms through which it can be used to achieve sustained competitive advantage. To close this gap, this study draws on the dynamic capability view to posit that a firm can attain sustained competitive advantage from its sensing, seizing and reconfiguring capabilities, which are manifested by the use of marketing analytics, marketing decision-making, and product development management. This study also examines the impact of the antecedents of marketing analytics use on marketing related processes. The analysis of a survey of 221 UK firm managers demonstrates: (a) the positive impact of marketing analytics use on both marketing decision-making and product development management; (b) the effect of the latter two on sustained competitive advantage; (c) the indirect effect of data availability on both marketing decision-making and production development management; and (d) the indirect effect of managerial support on marketing decision-making. The research model proposed in this study provides insights into how marketing analytics can be used to achieve sustained competitive advantage.

1. Introduction

Marketing analytics, which is a domain of business analytics (Holsapple, Lee-Post, & Pakath, 2014), refers to the collection, management, and analysis of data to extract useful insights to support marketing decision-making (Germann, Lilien, & Rangaswamy, 2013; Hanssens & Pauwels, 2016; Wedel & Kannan, 2016). While recent research indicates that the use of marketing analytics could have the potential to improve firm competitiveness and/or performance (e.g., CMO-Survey, 2016; Germann et al., 2013; Hanssens & Pauwels, 2016; Xu, Frankwick, & Ramirez, 2016), such a potential is still largely untapped, unexplored (Ariker, Diaz, Moorman, & Westover, 2015; McKinsey, 2016; Wedel & Kannan, 2016), and has yet to be substantiated (Germann et al., 2013). While the various conditions needed for using business analytics have not been sufficiently studied (Chen, Preston, & Swink, 2015; Trieu, 2017), it is not clear how business analytics could be used in order to improve decision-making and firm competitiveness and/or performance (Chen et al., 2015; Germann et al., 2013; Wedel & Kannan, 2016). Thus, more research with "deeper analysis" is needed (Sharma, Mithas, & Kankanhalli, 2014).

In order to advance our understanding of marketing analytics, this study seeks to answer two research questions. First and foremost, what are the mechanisms through which marketing analytics can be used to achieve firm competitiveness? Recent studies seem to have focused on the direct impact of marketing analytics use on firm competitiveness and/or performance (e.g., Germann et al., 2013; Xu et al., 2016) but paid little attention to explaining the mechanisms through which marketing analytics can be used to improve firm competitiveness (Wedel & Kannan, 2016). Several streams of research suggest that the link between the use of business analytics to firm competitiveness is rather complex (e.g., Tan, Guo, Cahalane, & Cheng, 2016). Conceptual research suggests that business analytics will first influence firm decision-making, which will in turn affect firm competitiveness and/or performance (Seddon, Constantinidis, Tamm, & Dod, 2017; Sharma et al., 2014). IT studies argue that the first order impacts of IT investment should be measured at managerial and operational processes (Barua, Kriebel, & Mukhopadhyay, 1995; Radhakrishnan, Zu, & Grover, 2008; Tallon, Kraemer, & Gurbaxani, 2000). Yet, to the best knowledge of the authors, no research has conceptualized, let alone empirically demonstrated, the mechanisms through which the use of marketing analytics can be linked to marketing related processes or capabilities and sustained competitive advantage.

In an attempt to make theoretical and empirical contributions to the literature, this study addresses the above research gap by developing a research model that explains how the use of marketing analytics is linked to marketing decision-making, product development management, and sustained competitive advantages, drawing on the dynamic capability view. Dynamic capabilities are "the firm's ability to integrate,

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build, and reconfigure internal and external competences to address rapidly changing environments" (Teece, Pisano, & Shuen, 1997, p. 516). Teece (2007) argued that dynamic capabilities comprise the capacity to (1) sense opportunities and threats, (2) seize opportunities, and (3) maintain competitiveness through reconfiguring resources. In the context of marketing analytics, dynamic marketing capabilities become key (Barrales-Molina, Martínez-López, & Gázquez-Abad, 2014), because they reflect a firm's ability to engage in market-based learning and further use the resulting insights to sense and seize opportunities, and to reconfigure the firm's resources and enhance its capabilities to attain sustained competitive advantage (Vorhies & Morgan, 2005) or superior performance (Morgan, 2012; Vorhies, Orr, & Bush, 2011). Nevertheless, as noted by Vorhies et al. (2011), "very little is known about how firms improve their marketing capabilities via the embedding of new market knowledge" (p.736). Thus, by extending the dynamic capability view to understanding the marketing analytics phenomenon, this study posits that a firm can attain sustained competitive advantage from its sensing, seizing and reconfiguring capabilities as manifested by the use of marketing analytics, marketing decision-making, and product development management.

Associated with the above, IT adoption and its determinants have long been considered critical to providing valuable insights for managers to make informed IT adoption decisions; however, the research results are mixed (Petter, Delone, & McLean, 2013; Sabherwal, Jeyaraj, & Chowa, 2006). With respect to the use of business analytics and its antecedents, more research is yet to be conducted to understand this relationship (Chen et al., 2015; Trieu, 2017). Hence, the second research question to be addressed is: whether and to what extent antecedent factors affect marketing analytics use, as well as marketing decision-making and product development management? Germann et al. (2013) found that a firm's top management team must not only commit adequate resources but also nurture a culture that supports the adoption of marketing analytics. Chen et al. (2015) studied the impact of business analytics on supply chain management and examined a few of its antecedents, such as technical compatibility, top management team support, expected benefits, competitive pressure, and organizational readiness. Although a few studies acknowledge that a number of antecedents are associated directly with the use of business/marketing analytics, little research exists to examine the indirect effect of antecedents on, for example, marketing decision-making and product development management. Therefore, this study seeks to extend extant analytics studies by developing a deeper understanding of antecedents' indirect effect on marketing related business processes.

The next section presents the study's overview of the theoretical underpinnings of its main concepts and proposed hypotheses. Then, the research methodology is discussed, including research design, sampling process, operationalization of constructs, and fieldwork, followed by the data analysis and presentation of results. Finally, theoretical and managerial implications, study limitations and directions for future research are provided.

2. Research hypotheses

The following section first expands on the relationships among the use of marketing analytics, marketing related processes, and sustained competitive advantage, drawing on the dynamic capability view. Next, it considers the indirect impacts of the four antecedents of marketing analytics use on marketing decision-making and product development management.

2.1. Use and outcomes of marketing analytics-a dynamic capability view

While the extent to which firms use marketing analytics, as well as their scopes of marketing activities (Hanssens & Pauwels, 2016), are expected to differ (e.g., Erevelles, Fukawa, & Swayne, 2016; Germann et al., 2013; Xu et al., 2016), marketing analytics can be used in a number of areas to inform marketing decisions (Ariker et al., 2015; CMO-Survey, 2015, 2016), to offer innovative ways to develop new products (Erevelles et al., 2016), and to improve firm competitiveness/performance (e.g., Germann et al., 2013; Hanssens & Pauwels, 2016).

Based on the dynamic capability view and in the context of this research, a firm can be expected to attain sustained competitive advantage from its sensing, seizing and reconfiguring capabilities as manifested by the use of marketing analytics, marketing decision-making, and product development management.

Firstly, the use of marketing analytics is seen to create "difficult-to-trade knowledge assets" (Teece et al., 1997, p.521) that mainly relate to customers' and competitors' domains (Bruni & Verona, 2009) and are part of the microfoundations of the firm's sensing capability (Teece, 2007), allowing the firm to gain valuable data-driven insights to sense threats and create opportunities. Such a view is consistent with prior research underpinned by the dynamic capability view. Chen et al. (2015) suggested that business analytics helps a firm establish knowledge creation routines, which are essential dynamic capabilities (Eisenhardt & Martin, 2000), to allow the firm to learn about customers, competitors, and the broader market environment (Wilden & Gudergan, 2015) thereby to increase its capability for strategic decision-making. Further, the authors maintained that while business analytics can be adopted by competitors, it becomes idiosyncratic across firms when it is embedded in, for instance, supply chain management. Likewise, Côrte-Real, Oliveira, and Ruivo (2017) noted that in order for a firm to create its knowledge resources from business analytics, it needs to be able to sense, acquire, process, store, and analyse the data and convert that data into knowledge, which enhances the firm's dynamic capability to continually renew its knowledge base and deliver business performance (Ambrosini & Bowman, 2009; Sher & Lee, 2004). Thus, it is conceivable that a firm's use of marketing analytics can help the firm to create its knowledge base thereby to enable the firm to better sense threats and opportunities.

Secondly, a firm's ability to use marketing analytics to sense opportunities and threats will provide input for the firm to seize the sensed opportunities through systematically identifying strategic marketing problems and opportunities, defining strategic marketing objectives and criteria for success, and developing and evaluating strategic alternatives. This prediction appears to be consistent with some evidence in the literature on business analytics. For instance, Cao, Duan, and Li (2015) showed that business analytics positively influences information processing capabilities, which in turn have a positive effect on decision-making effectiveness. Similarly, Chen et al. (2015) demonstrated that a firm's use of big data analytics enables the firm to have greater dynamic information processing capability, which allows the firm to reduce uncertainty by stimulating insights and knowledge creation, and to increase organizational capability for strategic decision-making. Research underpinned by the dynamic capability view also supports the above predication. As noted by Bruni and Verona (2009), market knowledge provides a shared view of future market trends and is highly influential in "resource allocation decisions that shape the strategic guidelines of future developments" (p. S110). In line with these findings, it seems plausible that a firm's use of marketing analytics to sense opportunities is expected to improve the comprehensiveness of marketing decisions thereby to seize the sensed opportunities.

Thirdly, a firm's use of marketing analytics to enhance its sensing and seizing capabilities could "lead to the augmentation of enterprise-level resources and assets" (Teece, 2007, p.1335). For example, reconfiguration may need to integrate resources for product development (Eisenhardt & Martin, 2000) to meet emerging market opportunities (Teece, Peteraf, & Leih, 2016), "integrate and combine assets including knowledge" or reconfigure "intangible assets to enable learning and the generation of new knowledge" (Teece, 2007, p.1339). In line with this, the firm's use of marketing analytics can be expected to improve its product development management that focuses upon the development and delivery of products or solutions (Slater & Narver, 2000; Srivastava, Fahey, & Christensen, 2001). There is precedence in the literature on business analytics to support this prediction. It is suggested that a firm can use business analytics to improve its ability to innovate (Kiron, Prentice, & Ferguson, 2012, Kiron, Prentice, & Ferguson, 2014), create products and services from analyses of data (Davenport, 2013a), or offer innovative ways to allow it to differentiate its products (Erevelles et al., 2016). A McKinsey report (Manyika et al., 2011) indicated that the use of big data analytics can help firms create new products and services, enhance existing ones, invent entirely new business models, reduce product development time by 20 to 50%, and offer opportunities to accelerate product development. In short, the use of marketing analytics could lead to better product development because it allows a firm to extract insights into customers' needs and expectations, as well as competitors' new designs, key-product features, and pricing strategies (Xu et al., 2016). Thus it is highly plausible to posit that using marketing analytics positively contributes to product development management.

Additionally, from the dynamic capability view, a firm's product development management is likely to be enhanced by its marketing decision-making. Barrales-Molina et al. (2014) suggested that new product development usually originates in sensing new market threats or opportunities; such market knowledge will then be incorporated into other decision processes. For example, Bruni and Verona (2009) suggested that the creation, use and integration of market knowledge and marketing resources in developing new drugs by pharmaceutical firms are highly influential in the initial phases of new drug development and become even more predominant during the pre- and post-launch stages of the drug development process. Therefore, drawing on the dynamic capability view and building upon relevant findings from the literature, the following three hypotheses are proposed.

H1. The use of marketing analytics relates positively to marketing decision-making.

H2. The use of marketing analytics relates positively to product development management.

H3. Marketing decision-making relates positively to product development management.

In order to further develop our understanding of the mechanisms through which marketing analytics can be used to enable a firm to improve its competitiveness, this study draws on the dynamic capability view to conjecture that a firm can attain sustained competitive advantage from its sensing, seizing and reconfiguring capabilities, as manifested by its use of marketing analytics, marketing decision-making, and product development management.

While little is known about how a firm can use dynamic marketing capabilities to gain sustained competitive advantage (Newbert, 2007, p. 142; Vorhies et al., 2011; Wilden & Gudergan, 2015), there is precedence in the literature to support the link between marketing decision-making and sustained competitive advantage. Eisenhardt and Martin (2000) suggested that “strategic decision making is a dynamic capability in which managers pool their various business, functional and personal expertise to make the choices that shape the major strategic moves of the firm” (p. 1107). Similarly, Slater, Olson, and Hult (2006) proposed that a firm's strategy formation capability is a dynamic capability that should lead to superior performance.

Likewise, marketing research suggests that marketing decision-making and firm competitiveness/performance is related (e.g., Atuahene-Gima & Murray, 2004; Cavusgil & Zou, 1994; Challagalla, Murtha, & Jaworski, 2014; Jocumsen, 2004; Keh, Nguyen, & Ng, 2007; Van Bruggen, Smidts, & Wierenga, 1998). However, Atuahene-Gima and Haiyang (2004) revealed that the direct link between marketing decision-making and firm performance is not significant, but it becomes significant when strategy implementation speed is higher. Moreover, Kim, Shin, and Min (2016) asserted that rather than its direct relationship with competitive advanatage, a firm's strategic marketing capability allows it to create a competitive new product. Thus, these marketing studies seem to suggest that marketing decision-making may be indirectly associated with competitiveness and/or performance.

With respect to the link between product development management and firm competitiveness/performance, research underpinned by the dynamic capability view suggests that product development management reflects a firm's seizing and reconfiguring capabilities that lead to sustained competitive advantage (Ambrosini & Bowman, 2009; Barrales-Molina et al., 2014; Eisenhardt & Martin, 2000; Helfat & Peteraf, 2009). For instance, Barrales-Molina et al. (2014) argued that new product development involves a firm renewing and reconfiguring its resources and capabilities, illustrated by how Apple has shaped itself and the market through continuous, regular introduction of new products (Teece, 2012) and how Intel has sustained its competitiveness by repeatedly developing new semiconductor chips for personal computers (Helfat & Winter, 2011).

At the same time, research suggests that dynamic capabilities are key mediators in creating competitiveness (e.g., Hsu & Wang, 2012; Marsh & Stock, 2006; Wang, Klein, & Jiang, 2007). Wang et al. (2007) demonstrated that IT support for knowledge management is positively associated with knowledge-based dynamic capabilities, which in turn are associated with firm competitiveness; and Hsu and Wang (2012) showed that dynamic capability mediates the impact of intellectual capital on performance. Additionally, marketing research suggests that marketing capabilities are at the heart of firm performance (e.g., Frösén & Tikkanen, 2016; Ramaswami, Srivastava, & Bhargava, 2009; Slater & Narver, 2000; Srivastava et al., 2001), such as product development management mediating the relationship between marketing orientation and firm performance (Jaakkola et al., 2016; Maydeu-Olivares & Lado, 2003; Naidoo, 2010). These studies are also seen to be consistent with research suggesting that business analytics will first influence process level performance such as decision-making processes, which will in turn affect organizational performance (e.g., Côrte-Real et al., 2017; Seddon et al., 2017; Sharma et al., 2014; Wamba et al., 2017).

Therefore, it seems highly plausible to postulate that marketing decision-making enhances product development management, which in turn leads to sustained competitive advantage. Thus, the following mediation hypothesis is proposed:

H4. The relationship between marketing decision-making and sustained competitive advantage is mediated through product development management.

2.2. The indirect impact of antecedents of marketing analytics use

Extant empirical research has suggested that the use of business/marketing analytics is affected by several antecedents (Chen et al., 2015;Germann et al., 2013; Gupta & George, 2016). For example, data availability is seen to be an important precursor to a firm's use of marketing analytics that may provide action possibilities for marketing decision-making (Germann et al., 2013; Gupta & George, 2016). Competitors' use of marketing analytics is also likely to stimulate the firm to use marketing analytics to capture market intelligence and improve its competitive position (Chen et al., 2015). However, the possibilities afforded by the use of marketing analytics and their associated values need to be first and foremost perceived and supported by the firm managers (Chen et al., 2015). A firm's choice of ensuring data availability and using marketing analytics is likely to be significantly influenced by whether its managers have recognized that data is a core strategic asset that enables the firm to make successful decisions and to differentiate its products (Davenport, 2013b; Erevelles et al., 2016; Kiron et al., 2014; Kiron, Ferguson, & Prentice, 2012; Lavalle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011; March & Hevner, 2007).

In addition to the direct impact of these antecedents on a firm's use of marketing analytics, they could have a deeper and indirect impact on the firm's marketing decision-making and product development management. While little research exists to examine this indirect effect of antecedents, empirical support for this notion can be found in other related areas in the literature that data availability may provide action possibilities for marketing decision-making (Germann et al., 2013; Gupta & George, 2016) or innovative ways to differentiate products (Erevelles et al., 2016), and that managers cognitions and perceptions influence successful IT implementation (Lin, Ku, & Huang, 2014) and innovation strategy and innovation outcomes (Talke, Salomo, & Kock, 2011). Thus, based on extant analytics studies (e.g., Chen et al., 2015; Germann et al., 2013; Gupta & George, 2016), it is plausible to posit that antecedents not only have a direct influence on the use of marketing analytics but also an indirect effect on marketing decision-making and product development management. Hence, this study extends previous analytics research by positing the following hypotheses:

H5. Data availability has an indirect effect through the use of marketing analytics on (a) marketing decision-making and (b) product development management.

H6. Managerial perception has an indirect effect through the use of marketing analytics on (a) marketing decision-making and (b) product development management.

H7. Managerial support has an indirect effect through the use of marketing analytics on (a) marketing decision-making and (b) product development management.

H8. Competitive pressure has an indirect effect through the use of marketing analytics on (a) marketing decision-making and (b) product development management.

Based on the dynamic capability view, Fig. 1 illustrates the study's proposed research model that articulates the predicted relationships. Primarily, the use of marketing analytics is posited to have a positive impact on marketing decision-making and product development management, which in turn have a positive impact on sustained competitive advantage. This study also suggests that marketing decision-making and product development management can be affected indirectly by data availability, managerial perception and support, and competitive pressure. The previous theoretical review and the study's hypotheses continue to inform the study's methodology, research design, and data analysis, presented in the following sections.

3. Research methodology

The hypotheses were tested empirically using SmartPLS that is recommended as well-suited for research situations where theory is less developed and formative constructs are part of the structural model (Gefen, Rigdon, & Straub, 2011; Hair, Ringle, & Sarstedt, 2013; Wetzels, Odekerken-Schröder, & van Oppen, 2009). Since research on marketing analytics is still emerging and the present study handles both reflective and formative constructs, SmartPLS is a suitable method to empirically test the research model.

3.1. Measures of constructs

The constructs listed in Table 1 were measured using scales adopted or further adapted from relevant items that were validated across a variety of studies. Both reflective and formative measurement models were used based on the four decision rules suggested by Petter, Straub, and Rai (2007): the direction of causality between construct and indicators, the interchangeability of indicators, the covariation among indicators, and the nomological net for the indicators.

3.1.1. Data availability

Data availability was measured formatively and its measures were directly adopted from Gupta and George (2016) in terms of 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.

3.1.2. Managerial perception

Four indicators for measuring managerial perception were adapted from prior studies (Kearns & Sabherwal, 2007; Liang et al., 2007). They measured the extent to which top management team: recognizes the strategic potential of marketing analytics, is knowledgeable about marketing analytics opportunities, is familiar with competitor's strategic use of marketing analytics, and believes marketing analytics contributes significantly to firm performance.

3.1.3. Managerial support

Three items were adapted from prior studies to measure managerial support in terms of the extent to which top management team creates support for marketing analytics initiatives and promotes the use of marketing analytics as a strategic priority (Chen et al., 2015; Germann et al., 2013; Liang et al., 2007).

3.1.4. Competitive pressure

Three items were adapted from Liang et al. (2007) to measure competitive pressure in terms of the extent to which a firm's

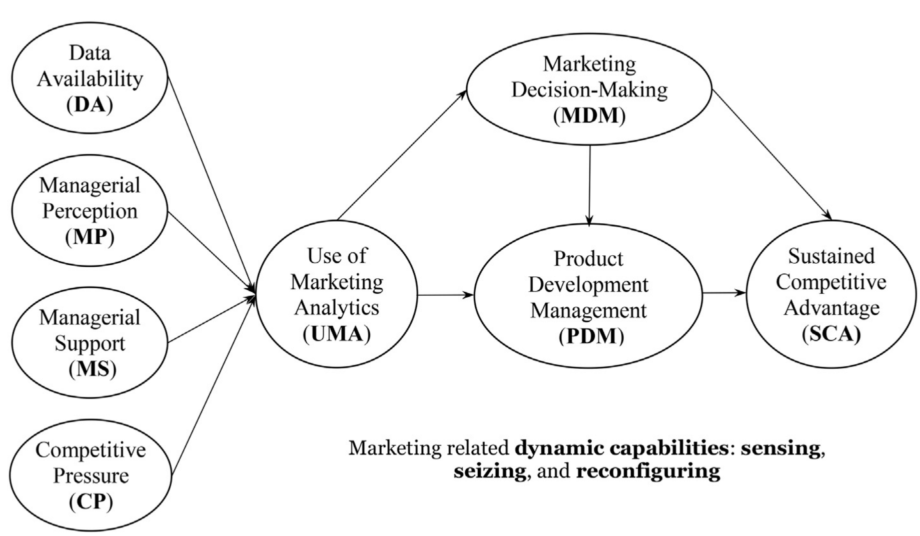

Fig. 1. Antecedents and Outcomes of Marketing Analytics Use.

Table 1
Constructs and indicators of the study.

Constructs	Indicators (based on Likert scale from 1- strongly disagree to 7-strongly agree)	Mean	S.D.
Data Availability (DA)	DA1-We have access to very large, unstructured, or fast-moving data for analysis	4.18	1.71
(Formative)	DA2-We integrate data from multiple internal sources into a data warehouse or mart for easy access	3.75	1.83
(Gupta & George, 2016)	DA3-We integrate external data with internal to facilitate high-value analysis of our business environment	3.70	1.76
Managerial perception (MP)	MP1-Top management team recognizes the strategic potential of marketing analytics	5.11	1.47
(Reflective)	MP2-Top management team is knowledgeable about marketing analytics opportunities	4.43	1.49
(Kearns & Sabherwal, 2007; Liang, Saraf, Qing, & Yajiong, 2007)	MP3-Top management team is familiar with competitor's strategic use of marketing analytics	3.85	1.47
	MP4-Top management team believes marketing analytics contributes significantly to firm performance	4.33	1.53
Managerial support (MS)	MS1-Top management team promotes the use of marketing analytics in your company	4.05	1.66
(Reflective)	MS2-Top management team creates support for marketing analytics initiatives within your company	4.14	1.63
(Chen et al., 2015; Germann et al., 2013; Liang et al., 2007)	MS3-Top management team has promoted marketing analytics as a strategic priority within your company	3.81	1.67
Competitive pressure (CP) (Formative) (Liang et al., 2007)	CP1-Our competitors have implemented marketing analytics to collect, manage, and analyse data to extract useful insights	4.47	1.45
	CP2-Our suppliers have implemented marketing analytics to collect, manage, and analyse data to extract useful insights	4.29	1.54
	CP3-Our customers have implemented marketing analytics to collect, manage, and analyse data to extract useful insights	4.17	1.62
Use of marketing analytics (UMA)*	Customer-related (lower-order construct)		
(Higher-order)	UMA1-Customer insight	3.62	1.55
(Formative)	UMA2-Customer acquisition	3.41	1.61
(Ariker et al., 2015; CMO-Survey, 2015, 2016)	UMA3-Customer retention	3.51	1.58
	UMA4-Segmentation	3.24	1.67
	Product-related (lower-order construct)		
	UMA5-New product or service development	3.58	1.67
	UMA6-Product or service strategy	3.49	1.62
	UMA7-Promotion strategy	3.42	1.63
	UMA8-Pricing strategy	3.41	1.72
	UMA9-Marketing mix	3.34	1.64
	UMA10-Branding	3.57	1.65
	General marketing-related		
	UMA11-Digital marketing	3.73	1.68
	UMA12-Social media	3.66	1.68
	UMA13-Multichannel marketing	3.10	1.68
Marketing decision-making	MDM1-Develop many alternative courses of action to achieve the intended objectives?	4.32	1.49
(MDM)	MDM2-Conduct multiple examinations of any suggested course of action the project members wanted to take?	3.98	1.50
(Reflective)			
(Atuahene-Gima & Murray, 2004; Chng, Shih, Rodgers, & Song, 2015)	MDM3-Thoroughly examine multiple explanations for the problems faced and for the opportunities available?	4.22	1.50
	MDM4-Search extensively for possible alternative courses of action to take advantage of the opportunities?	4.22	1.51
	MDM5-Consider many different criteria before deciding on which possible courses of action to take to achieve your intended objectives?	4.43	1.47
Product development management (PDM)	PDM1-We have the ability to develop new products/services	5.69	1.30
(Reflective)	PDM2-We are able to commercialize ideas fast	5.03	1.55
(Frösén & Tikkanen, 2016)	PDM3-We have a number of product/service innovations	5.34	1.42
	PDM4-We are able to successfully launch new products/services	5.36	1.32
	PDM5-We are able to achieve productivity gains from R&D investments	4.62	1.58
Sustained competitive advantage (SCA)	Over the past five years,		
(Reflective)	SCA1-We were more profitable than our key competitors	4.78	1.34
(Im & Workman Jr, 2004; Prajogo & Oke, 2016)	SCA2-Our sales increased faster than our key competitors	4.60	1.36
	SCA3-Our market share increased faster than our key competitors	4.59	1.37
	SCA4-We had better return on investment than our key competitors	4.66	1.30

* -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.

competitors, suppliers and customers have implemented marketing analytics to collect, manage, and analyse data to extract useful insight. While the original three items developed by Liang et al. (2007) were reflective, this study used them as formative items based on the four decision rules suggested by Petter et al. (2007).

3.1.5. Use of marketing analytics

So far, few studies have measured and validated the use of marketing analytics specifically, except that Germann et al. (2013) defined "deployment of analytics" using three items to measure its average use. Instead, this study intended to measure the extent to which marketing analytics has been used in 13 different areas of marketing decisions, based on items reported by CMO-Surveys (2015, 2016). In order to define a formative construct meaningfully, it is extremely important that all facets of the construct should be captured (Diamantopoulos & Winklhofer, 2001). To meet this requirement, the use of marketing analytics could be measured comprehensively by using the 13 marketing decision areas based on CMO-Surveys (2015, 2016): customer insight, customer acquisition, digital marketing, customer retention, branding, social media, segmentation, promotion strategy, new product or service development, product or service strategy, pricing strategy, marketing mix, and multichannel marketing. However, these 13 areas have not been validated by academic research yet; and it does not seem to be conceptually meaningful to use them directly to measure the use of marketing analytics as they refer to several distinctive types of marketing decision activities. A more appropriate measuring approach, then, is to define a higher-order formative construct by several lower-order formative constructs, each of which can be defined by several distinctive items (Hair, Hult, Ringle, & Sarstedt, 2014). As a result, the 13 areas were divided into customer-related use of marketing analytics in the areas of customer insight, customer acquisition, customer retention, and segmentation; product-related 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 that is a part of new product lunch strategy (Hultink, Griffin, Hart, & Robben, 1997), "critical determinant of new product success" (Truong, Klink, Simmons, Grinstein, & Palmer, 2017, p.85); and general marketing-related use of marketing analytics in relation to digital marketing, social media, and multichannel marketing.

3.1.6. Marketing decision-making

Marketing decision-making was measured by adapting five items based on Atuahene-Gima and Murray (2004) and Chng et al. (2015). The items covered the extent to which a firm develops many alternative courses of action to achieve the intended objectives, conducts multiple examinations of any suggested course of action, thoroughly examines multiple explanations for the problems faced and for the opportunities available, searches extensively for possible alternative courses of action to take advantage of the opportunities, and considers several different criteria before deciding on which possible courses of action to take.

3.1.7. Product development management

Product development management was measured using items adapted from Frösén and Tikkanen (2016) to address the extent to which a firm has the ability to develop new products or services, commercialize ideas fast, have a number of product or service innovations, successfully launch new products or services, and achieve productivity gains from R&D investments.

3.1.8. Sustained competitive advantage

Sustained competitive advantage was measured based on respondent's perceived performance relative to its key competitors over the past five years using four items adapted from prior studies (Im & Workman Jr, 2004; Prajogo & Oke, 2016). Perceptual measures, while widely used in organizational research, were preferred in this research because "the heterogeneous sample produce significant differences in capital structures and accounting conventions" (Powell, 1995, p.25). While the use of perceptual measures for sustained competitive advantage may be questioned in terms of their validity; past studies have shown that this approach is consistent with objective performance measures (e.g., Germann et al., 2013; Newbert, 2008; Prajogo & Oke, 2016).

3.1.9. Control variables

Additionally, this study followed prior analytics studies in controlling for firm size (number of employees) and industry type (e.g., Côrte-Real et al., 2017; Germann et al., 2013; Gupta & George, 2016). Firm size may explain the fact that larger firms could benefit from economies of scale and scope, rendering their use of marketing analytics more effective. Industry type may account for differences across industry segments. Consistent with management studies in other areas (e.g., Ohlott, Ruderman, & McCauley, 1994; Sousa & Bradley, 2006), respondent's job tile and tenure in the industry were also controlled for as they may affect respondent's perception of marketing analytics use. All control variables were categorical in this research and measured by the use of dummy variables.

3.2. Sample and data collection

In order to test the above hypotheses, primary data was collected from a sample of UK firms using a questionnaire survey. Data was analyzed using structural equation modeling. Such a methodological approach has been frequently used by analytics studies underpinned by the dynamic capability view (e.g., Germann et al., 2013; Wamba et al., 2017) and is seen to be an appropriate research method for conducting research with marketing managers (e.g., Deshpande & Webster Jr, 1989; Lukas, Whitwell, & Heide, 2013; Marta et al., 2013; Ramaseshan, Ishak, & Rabbanee, 2013). A key informant approach was used to collect data (Bagozzi, Youjae, & Phillips, 1991). A convenience sample of senior and middle managers of UK firms was drawn from the FAME (Financial Analysis Made Easy) database as managers were highly likely to be involved in both marketing analytics and decision-making processes.

Dillman's total design method (Dillman, 1978) was utilized to design the survey by following the suggestion that "recipients are most likely to respond if they expect that the perceived benefits of doing so will outweigh the perceived costs of responding" (Dillman, 1991, p. 233). Specifically, the reduction of perceived costs, increasing perceived rewards, and increasing trust were considered. The perceived cost was reduced by including an anonymous hyperlink link in the e-mail to allow respondents to conveniently take the survey noting that they can complete it in about 10 min. Further, each respondent was offered an executive summary of the results and the opportunity to enter into a draw to win one of five Amazon gift certificates (£100 each). To increase recipients' trust, the first e-mail survey included a personalized cover letter outlining the purpose of the study, the study's social usefulness, reassurance of anonymity, a specific instruction guide, and an indication that this survey was conducted by academic members from a UK University.

To capture the responses to the measurements of all constructs, the questionnaire survey was generated using a seven-point Likert scale (ranging from 1-strongly disagree to 7-strongly agree, except where shown otherwise in Table 1). The questionnaire covered (a) respondent and company profile, (b) antecedents to the use of marketing analytics, (c) the use of marketing analytics, (d) marketing decision-making, (e) product development management, and (f) perceived competitive advantage. Table 1 shows the questions used in the survey to measure the research constructs. The survey was then scrutinized by subject experts. After a few revisions, the survey was tested with five academic experts to ensure that the respondents understood the questions and there were no problems with the wording or measurements. This resulted in a number of formatting and presentation modifications. The survey questionnaire was then distributed to managers electronically through Qualtrics, an online survey tool. The survey recipients were also reminded to pass the survey to another manager if they believed that he/she was in a better position to answer the survey questions. Four rounds (the survey plus three follow-ups), one-week apart, of emails with the questionnaire survey were conducted.

Using Qualtrics software, a total of 36,970 survey invitations were sent by email and 3053 were subsequently bounced for a variety of unknown reasons, which could include the receiving inbox being full, nonexistent email address, the recipient server having a high security firewall, or the recipient server being offline. Of all sent emails, 416 surveys were started; of these, 242 responses were received while 221 were usable responses. When non-probability samples are used, instead of calculating a response rate, a completion rate is more informative and is calculated as the proportion of those who have started and then completed the survey (Callegaro & Disogra, 2008; Eysenbach, 2004). In line with this, the completion rate for this survey was 58.2%.

While a response rate was not calculated, this study instead considered the number of responses from the perspective of building an adequate model (Couper, 2000). In the structural model, the maximum number of arrows pointing at a construct is four. In order to detect a minimum R^2 value of 0.10 in any of the constructs at a significance level of 1%, the minimum sample size required is 191 (Hair et al., 2014). Since 221 usable responses were received, this minimum sample size requirement was thus met.

Table 2
Respondent Profiles (n = 221).

Industry	%	Respondent Positions	%	Respondent Experience Years (x) in the industry (%)
Manufacturing	18.1	CEO/President/MD/Partner	59.1	$x \leq 5$ (10.9)
Prof Services	12.9	Vice President/Director	8.8	$5 < x \leq 10$ (10.3)
Retail/Wholesale	6.9	Chief Marketing Officer	3.7	$10 < x \leq 15$ (8.0)
Technology	9.7	Other C-level Executive	4.3	$15 < x \leq 20$ (13.2)
Fin Services	5.7	Director/Head of Marketing	10.5	$20 < x \leq 25$ (12.6)
Other	46.7	Other directors	13.6	$x > 25$ (45.0)

Table 3
Expected and observed value.

Company size	Observed value N	Expected value N	Residual
1–9	44	37	7
10–49	65	54	11
50–249	78	65	13
250 or more	34	29	5
chi-square test: p-value = .07			

3.3. Respondents

Table 2 summarizes the respondents' characteristics in terms of their organizational positions and years of industry experience. A key informant approach (Bagozzi et al., 1991) was used to collect data. The reported positions of the respondents suggested that 59.1% of the respondents were in a senior managerial position and the rest of them were in a middle managerial position. Based on their position within the firm, the respondents were considered to have relevant knowledge and experience to be able to address the survey questions.

Of all respondents, almost 89% had been in their industries for more than five years; of these 89%, 45% for > 25 years. The respondents included 18.1% from the manufacturing sector, 12.9% from professional services, 9.7% from technology, 6.9% from retail/wholesale, and 5.7% from financial services. Of all 221 respondents, 44 (20.1%) were from firms with < 10 employees, 65 (29.2%) were from firms with more than nine but < 50 employees, 78 (35.1%) were from firms with > 49 but < 250 employees, and 34 (15.6%) were from companies with > 250 employees.

3.4. Common method and non-respondent bias

The extent of common method bias, which may compromise the validity of research conclusions (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003) or the true correlations between variables and cause biased parameter estimates (Malhotra, Patil, & Kim, 2007), was assessed with three tests. The first was a procedural remedy to improve scale items through defining them clearly and keeping the questions simple and specific. In addition, every point on the response scale was labeled, helping reduce item ambiguity (Krosnick, 1999). Positively and negatively worded measures were also used to control for acquiescence and disacquiescence biases (Podsakoff, MacKenzie, & Podsakoff, 2012).

The second test was Harman's single-factor analysis, which was conducted to assess whether the common method variance associated with the data was high by entering all independent and dependent variables (Podsakoff et al., 2003). The test result indicated that the first factor accounted for 13.81% of the total variance; thus, there was no evidence of a substantial respondent bias in this study.

Finally, the correlation matrix (Table 5) was checked to identify if there were any highly correlated factors (highest correlation r = 0.767). Since common method bias should have resulted in extremely high correlations (r > 0.90) as suggested by Pavlou, Huigang, and Yajiong (2007), the result indicated that this study did not suffer from common method bias.

To evaluate the presence of non-response bias, two tests were conducted. First, a t-test was conducted to compare early (n = 149) and late (n = 72) respondents on all measures. It is expected that early respondents represent the average respondent while late respondents represent the average non-respondent (Armstrong & Overton, 1977). The t-test results did not find significant differences between the two respondent groups, suggesting an absence of non-response bias.

As a second test for non-response bias, and based on the known value for the population approach (Armstrong & Overton, 1977), the distribution of the company size of the respondents was compared with that of the complete sampling frame. In Table 3, the observed value corresponds to the number of the responding firms while the expected value denotes the number of all firms from the full sampling frame generated from FAME. A nonparametric chi-square test comparing the distributions of the observed and expected values found that there were no significant differences between respondents and non-respondents.

3.5. Data screening

Data screening was performed using SPSS22. Observations where the missing data exceeded 10% were removed (Hair, Black, Babin, & Anderson, 2010), reducing the 242 responses to 221. The remaining data set still had missing values but < 5% on a single variable, which is not a major concern (Amabile, 1983) if the values are missing completely at random (MCAR) (Hair et al., 2010). Little's MCAR test was conducted to check if the remaining missing data were MCAR and the result was insignificant. Thus, all 221 responses were retained while responses with missing values were replaced by using the mean value replacement.

3.6. Evaluation of the measurement model

The reflective measurement model was evaluated and validated by considering the internal consistency (composite reliability), indictor reliability, convergent validity and discriminant validity (Hair et al., 2014). The evaluation results are summarized in Table 4 and Table 5.

3.7. Assessment of formative measurement model

The formative measurement model was evaluated in terms of multicollinearity, the indicator weights, significance of weights, the indictor loadings (Hair et al., 2014), and nomological validity (MacKenzie, Podsakoff, & Podsakoff, 2011). To assess the level of multicollinearity, the values of variance inflation factor (VIF) of all formative constructs were evaluated. There were no major collinearity issues since all VIF values were below 3, < 3.3, the threshold value suggested for VIF by Petter et al. (2007).

Based on bootstrapping (5000 samples), all formative indictors' outer loadings, outer weights and the associated significance testing p-values were assessed, summarized in Table 6. All indicators' outer weights were significant, except four of them were not but their outer loadings were either above the suggested threshold of 0.5 or

Table 4
Convergent validity and internal consistency reliability.

Construct	Indicator	Loading	Indicator reliability	Composite reliability	Cronbach's α	AVE
MP	MP1	0.81	0.66	0.89	0.84	0.68
	MP2	0.82	0.67			
	MP3	0.78	0.61			
	MP4	0.87	0.76			
MS	MS1	0.95	0.90	0.97	0.95	0.91
	MS2	0.96	0.92			
	MS3	0.94	0.88			
MDM	MDM1	0.77	0.59	0.93	0.91	0.73
	MDM2	0.89	0.79			
	MDM3	0.91	0.83			
	MDM4	0.84	0.71			
	MDM5	0.86	0.74			
PDM	PDM1	0.77	0.59	0.89	0.85	0.63
	PDM2	0.77	0.59			
	PDM3	0.82	0.67			
	PDM4	0.85	0.72			
	PDM5	0.74	0.55			
SCA	SCA1	0.81	0.66	0.93	0.89	0.76
	SCA2	0.92	0.85			
	SCA3	0.91	0.83			
	SCA4	0.84	0.71			

Table 6
Outer weights & significance testing results.

Constructs	Indicators	Out weights	Out loading
CP	CP1	0.564*	0.807***
	CP2	0.04ns	0.645***
	CP3	0.622***	0.836***
DA	DA1	0.152ns	0.478***
	DA2	0.229ns	0.793***
	DA3	0.772***	0.966***
UMA	UMA1	0.075**	0.802***
	UMA2	0.099***	0.799***
	UMA3	0.061*	0.75***
	UMA4	0.157***	0.85***
	UMA5	0.102***	0.768***
	UMA6	0.117***	0.841***
	UMA7	0.109***	0.856***
	UMA8	0.002ns	0.701***
	UMA9	0.189***	0.905***
	UMA10	0.056**	0.799***
	UMA11	0.036*	0.747***
	UMA12	0.054***	0.758***
	UMA13	0.146***	0.867***

*** $p < .001$.
** $p < .01$.
* $p < .05$, ns = not significant.

statistically significant (Hair et al., 2014).

To assess the nomological validity of formative constructs, MacKenzie et al. (2011) suggested to test whether the focal construct is significantly related to other constructs in its nomological network, and the relationship between the formative construct and other theoretically related constructs in the research model should be strong. By examining the structural paths (Fig. 2), the results indicated positive and highly significant relationships among all three formative constructs and other reflective constructs in the model, thus indicating the nomological validity of the three formative constructs. Therefore, based on the above evaluations, the formative measurement model was valid.

To understand whether sustained competitive advantage was affected by other variables, this study controlled firm size, industry type, job title and tenure by the use of dummies. However, none of the control variables had a statistically significant effect in this research context.

The predictive power of the model was assessed by the amount of variance attributed to the latent variables (i.e., R^2). The R^2 values indicate that the full model explains 48.7% of the variance in UMA, 23.3% in MDM, 13.9% in PDM, and 24.2% in SCA. When PLS is used, the effect size suggested for R^2 in IT-related research is small = 0.1, medium = 0.25, and large = 0.36 (Wetzels et al., 2009). In line with this, the effect size of UMA was large; and the effect sizes of MDM and SCA were close to medium; and the effect size of PDM was small.

3.8. Hypotheses testing and mediation analysis

Table 7 shows the results of hypothesis testing. H1 and H2 propose that UMA (use of marketing analytics) is positively associated with MDM (marketing decision-making) and PDM (product development management); they are supported as UMA's effect on MDM and PDM are 0.482 ($p < .001$) and 0.194 ($p < .05$) respectively. H3 assumes that MDM is positively related to PDM, which is confirmed by MDM's effect of 0.238 ($p < .01$) on PDM.

H4 posits that MDM has a positive effect on SCA (sustained competitive advantage) through the mediating role of PDM. To verify H4, the mediating role of PDM on the relationship between MDM and SCA was analyzed based on bootstrapping (5000 samples) (Hair et al., 2014; Hayes, 2009; Preacher & Hayes, 2004). The analysis indicated that while MDM's direct effect on SCA is not significant, its indirect effect on SCA is 0.141 ($p < .001$), suggesting that PDM mediates the effect of MDM on SCA. Thus, H4 is supported.

While all antecedents each have a significant direct effect on UMA, their indirect effects via UMA on MDM and PDM vary. H5 posits that DA (data availability) has an indirect effect on (a) MDM and (b) PDM, which is supported as DA has an indirect effect (a) of 0.158 ($p < .001$) on MDM and (b) of 0.101 ($p < .001$) on PDM. H6 assumes that MP (managerial perception) has an indirect effect on (a) MDM and (b) PDM, which is rejected as MP has no statistically significant indirect effect on either MDM or PDM. H7 postulates that MS (managerial support) has an indirect effect on (a) MDM and (b) PDM. While MS's indirect effect on MDM is supported, its indirect effect on PDM is not. H8 assumes that CP (competitive pressure) has an indirect effect on (a) MDM and (b) PDM, which is rejected as CP has no statistically significant indirect effect on either MDM or PDM.

Table 5
Descriptive statistics, correlations, and average variance extracted.

	Mean	S.D.	CP	DA	MP	MS	MDM	PDM	SCA	UMA
CP	4.32	1.14	#							
DA	3.77	1.54	0.37**	#						
MP	4.41	1.23	0.27**	0.49**	0.82					
MS	4.00	1.57	0.29**	0.58**	0.77**	0.95				
MDM	4.23	1.28	0.13	0.45**	0.35**	0.36**	0.86			
PDM	5.19	1.13	0.08	0.22**	0.28**	0.18**	0.33**	0.79		
SCA	4.65	1.16	−0.01	0.18**	0.21**	0.21**	0.15*	0.43**	0.87	
UMA	3.42	1.36	0.36**	0.60**	0.55**	0.61**	0.48**	0.31**	0.23**	#

#Formative; **-significant correlations at the $p < .01$ level, * at $p < .05$ level (two-tailed); the diagonal elements (in bold) represent the square root of AVE.

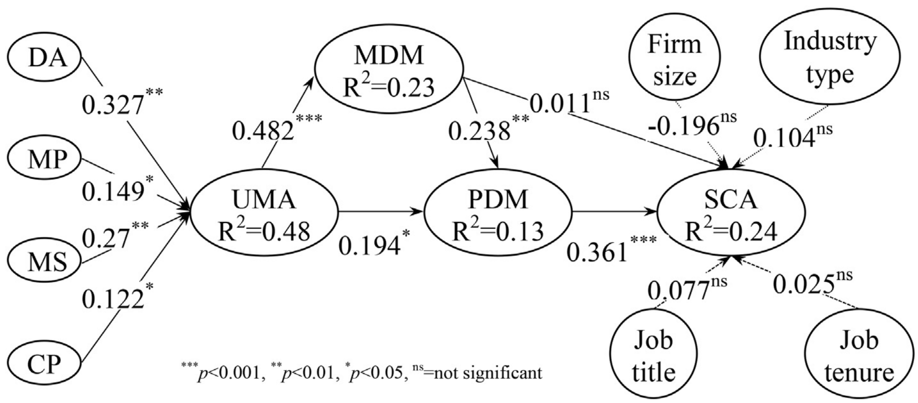

Fig. 2. Hypothesis test results.

4. Discussion and conclusions

4.1. Discussion

Research suggests that the use of marketing analytics could have the potential to improve the firm competitiveness and/or performance; thus, understanding the mechanisms through which such potentials can be realized, as well as the conditions of using marketing analytics, is central both to firms and scholarly research. In this context, even though it has been suggested that the link between the use of business/marketing analytics to firm competitiveness is rather complex (e.g., Tan et al., 2016), there is limited theoretical and empirical understanding about this relationship. The gap is especially pronounced and little academic investigation is undertaken considering the ways in which the use of marketing analytics can be linked to firm competitiveness (Germann et al., 2013; Trieu, 2017; Wedel & Kannan, 2016). This study drew on the dynamic capability view and examined: (a) the effect of marketing analytics use on marketing decision-making (H1) and product development management (H2); (b) the effect of marketing decision-making on product development management (H3); and the indirect relationship between marketing decision-making and sustained competitive advantage mediated by product development management (H4); (c) whether and to what extent data availability (H5), managerial perception (H6), managerial support (H7), and competitive pressure (H8) each have indirect influence on marketing decision-making and product development management through the use of marketing analytics.

The study's outcomes suggest that the use of marketing analytics positively affects marketing decision-making (with a path coefficient of 0.482 at $p < .001$), and product development management directly (with a path coefficient of 0.194 at $p < .05$) and indirectly (indirect effect of 0.115 at $p < .01$). This study also shows that marketing decision-making has no direct but an indirect positive effect (0.141, at $p < .001$) on sustained competitive advantage through the mediating role of product development management. The findings, while they are consistent with the research on the direct relationship between marketing analytics use and firm competitiveness/performance (e.g., CMO-Survey, 2016; Germann et al., 2013; Xu et al., 2016), explicate the ways in which the use of marketing analytics leads to sustained competitive advantage, which has so far been largely unexplored (Germann et al., 2013; Trieu, 2017; Wedel & Kannan, 2016). The study's findings provide both conceptual and empirical evidences in support of prior studies regarding the complex relationship between marketing analytics and firm performance (e.g., Tan et al., 2016), and the influence of business analytics on the decision-making process, which in turn affects organizational performance (Seddon et al., 2017; Sharma et al., 2014), as well as the first order impacts of IT investment measured at managerial and operational processes (Barua et al., 1995; Radhakrishnan et al., 2008; Tallon et al., 2000). Moreover, the findings support the literature on marketing-related business capabilities which considers product development management at the heart of firm performance (e.g., Frösén & Tikkanen, 2016; Jaakkola et al., 2016; Ramaswami et al., 2009; Slater & Narver, 2000; Srivastava et al., 2001).

With respect to the impact of antecedents of marketing analytics use, the findings show all antecedents tested in this study have a direct effect on the use of marketing analytics, which provides additional empirical evidence in support of the findings from Germann et al. (2013) and Chen et al. (2015). More importantly, the findings indicate that two antecedents have varying indirect effects on marketing related processes via the use of marketing analytics. Specifically, data availability has an indirect effect on both marketing decision-making and product development management, while managerial support has an indirect effect on marketing decision-making but not on product development management. These findings appear to provide empirical evidence to support the view that data availability and managerial support as antecedents may have a deeper effect on how business

Table 7
Summary results of hypotheses testing.

Hypothesis	Hypothesized Path	Direct or indirect effect	Empirical evidence
H1	UMA - > MDM	0.482*** (direct)	Yes
H2	UMA - > PDM	0.194* (direct)	Yes
H3	MDM - > PDM	0.238** (direct)	Yes
H4	MDM - > PDM - > SCA	0.141***(indirect)	Yes
H5a	DA - > UMA - > MDM	0.158*** (indirect)	Yes
H5b	DA - > UMA - > PDM	0.101*** (indirect)	Yes
H6a	MP - > UMA - > MDM	0.072^{ns} (indirect)	No
H6b	MP - > UMA - > PDM	0.046^{ns} (indirect)	Yes
H7a	MS - > UMA - > MDM	0.130** (indirect)	Yes
H7b	MS - > UMA - > PDM	0.083^{ns} (indirect)	No
H8a	CP - > UMA - > MDM	0.059^{ns} (indirect)	No
H8b	CP - > UMA - > PDM	0.038^{ns} (indirect)	No

analytics can be used to enhance firm competitiveness or performance (Trieu, 2017). These findings could be interpreted in accordance with the view that data is the basis for informing decision-making (Wedel & Kannan, 2016) and a new capital that offers a firm innovative ways to differentiate its products (Erevelles et al., 2016). These effects are believable, especially to managers who perceive that data is "the new oil, the new soil, the next big thing, and the force behind a new management revolution" (Ransbotham, Kiron, & Prentice, 2016, p.1). However, contrary to expectation, both managerial perception and competitive pressure have no statistically significant indirect effect on marketing decision-making and product development management. On the whole, this study's findings about both the direct and indirect effects of antecedents appear to extend existing analytics research on the conditions required for the use of marketing analytics.

4.2. Theoretical contributions

This study offers several contributions that improve the theoretical understanding of the conditions surrounding marketing analytics use in the context of dynamic marketing capabilities.

Firstly, this study integrates the dynamic capability view with marketing analytics research to advance our understanding of the mechanism through which firm competitiveness stems from dynamic marketing capabilities. While prior research suggests that dynamic marketing capabilities become central to attaining sustained competitive advantage (Barrales-Molina et al., 2014; Vorhies & Morgan, 2005), fundamentally, very little is known about how this can be achieved (Vorhies et al., 2011; Wilden & Gudergan, 2015). This study is one of only a small number of studies that finds empirical evidence to show that sensing, seizing and reconfiguring capabilities, as manifested by the use of marketing analytics, marketing decision-making, and product development management, have a significant positive effect on sustained competitive advantage. By extending the dynamic capability view to the marketing analytics phenomenon and developing an understanding of the mechanism through which sustained competitive advantage can be gained from dynamic marketing capabilities, this study makes a significant contribution to the under-examined research on dynamic marketing capabilities (Vorhies et al., 2011; Wilden & Gudergan, 2015) in particular and on dynamic capability (Newbert, 2007; Vorhies et al., 2011; Wilden & Gudergan, 2015) in general. Additionally, while prior research suggests that little is known about how firms improve their marketing capabilities based on market knowledge (Vorhies et al., 2011), this study contributes to the marketing literature by showing that a firm can improve its sensing, seizing and reconfiguring capabilities by using marketing analytics, making comprehensive marketing decisions, and managing product development.

Secondly, this study contributes to the growing literature on business/marketing analytics in two ways. Although scholars (e.g., Jaakkola et al., 2016; Seddon et al., 2017; Sharma et al., 2014) have speculated that the relationship between analytics use and its impact on firm competitive/performance is a complex process, this study may be among the first to have conceptualized and empirically tested a research model that relates the use of marketing analytics to marketing decision-making, product development management, and sustained competitive advantage. Additionally, this study advances our understanding of the impact of the conditions needed for the use of business analytics, which is insufficiently studied (Chen et al., 2015; Trieu, 2017). Whereas prior studies have focused on understanding the direct effects of antecedents on the use of business/marketing analytics (e.g., Chen et al., 2015; Germann et al., 2013; Gupta & George, 2016), little research exists to investigate the indirect effects. The findings, in addition to confirming the direct effect of antecedents on the use of marketing analytics, extend prior analytics study outcomes by showing the indirect impact of data availability on both marketing decision-making and new product development, as well as that of managerial support on marketing decision-making.

Thirdly, this study contributes to the marketing literature by advancing our understanding of the complex relationships among marketing decision-making, product development management, and sustained competitive advantage. Although marketing scholars have suggested that sustained competitive advantage can be gained from either marketing decision-making or product development management (e.g., Atuahene-Gima & Haiyang, 2004; Kim, Im, & Slater, 2013), such interrelationship has not been specifically modeled or tested in the literature. The present study may be among the first to have hypothesized and empirically confirmed that product development management uniquely mediates the relationship between marketing decision-making and sustained competitive advantage. This casts fresh light on refining our understanding of extant marketing research.

4.3. Managerial implications

Furthermore, the research model developed in this study has significant managerial implications. Firstly, firms wishing to improve their marketing decision-making and attain sustained competitive advantage can orient their strategies toward proactively responding to competitive pressures while simultaneously developing favorable internal conditions for the effective use of marketing analytics. Secondly, the research model allows a firm to appreciate the significance of the use of marketing analytics to improve its marketing processes and dynamic capabilities thereby to gain sustained competitive advantage. Thirdly, the research model allows a firm to be aware that using marketing analytics to improve its competitiveness is a complex process that involves developing and maintaining a set of favorable conditions. Fourthly, the significant and positive effects of using marketing analytics on strategic decision-making, improved product development management and sustained competitive advantage provide incentives for firms to invest in marketing analytics. Finally, the salience of marketing analytics use in firms suggests that it is important for a firm's top management team to support developing and maintaining organizational analytics capability and guard against the vices that threaten such applications.

4.4. Limitations and future research

Any conclusions drawn from this study should be considered in light of several limitations, some of which provide avenues for future research. Firstly, the present study focuses on developing an understanding of the ways in which marketing analytics can be used to attain sustained competitive advantage. Hence, it does not (and was not intended to) capture all the key factors, such as environmental dynamism, that may affect the relationship between marketing analytics use and sustained competitive advantage. Thus, caution should be taken when interpreting the research results. Additional work could include additional control variables to further test the validity and usefulness of this research model.

Secondly, although non-probability sample is commonly used in the marketing field (e.g., Barwise, 1993; Diamantopoulos, 2005), it does limit the generalizability of the study's findings. While non-probability sampling methods are frequently used as an acceptable alternative to probability sampling, there seems to be no generally accepted model for evaluating the quality of non-probability sampling. Hence one interesting future research topic is to develop a coherent framework and accompanying set of measures for evaluating the quality of non-probability samples.

Thirdly, while the analysis uses perceptual measures to demonstrate that firms can attain sustained competitive advantage from a complex chain relating the antecedents, use and outcomes of marketing analytics, past studies have shown that this approach is consistent with objective measures (e.g., Germann et al., 2013; Newbert, 2008; Prajogo & Oke, 2016). Obtaining objective data to complement perceptual measures would thus be useful.

Fourthly, the current research results are based on and limited to UK firms. It would be worthwhile to extend this work to firms in other countries. Finally, this research is quantitative and based on survey data to examine relationships between study concepts. Future research could be based on qualitative data to develop richer and deeper understanding of how and why marketing analytics can be used to improve marketing decision-making, marketing related business processes, and sustained competitive advantage.

4.5. Conclusion

Drawing on the dynamic capability view, this study has articulated and tested a research model for understanding the mechanisms through which the use of marketing analytics is linked to sustained competitive advantage. Most importantly, the current study reinforces the premise that the use of marketing analytics can lead to improved marketing decision-making and firm competitiveness. Notwithstanding the complexity of unraveling the interplay among the use of marketing analytics, marketing decision making, product development, and sustained competitive advantage, this study provides a research model that can help firms understand and effectively use marketing analytics.

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