Traditional Marketing Analytics, Big Data Analytics, Big Data System Quality and the Success of New Product Development

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Citation Reference:

Aljumah, A., Nuseir, M., & Alam, M.M. (2021). Traditional Marketing Analytics, Big Data Analytics and Big Data System Quality and the Success of New Product Development. *Business Process Management Journal*, 27(4), 1108-1125. (online) <https://doi.org/10.1108/BPMJ-11-2020-0527>

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Abstract

Objective/Purpose: This study investigates the impact of traditional marketing analytics and big data analytics on the success of a new product. Moreover, it assesses the mediating effects of the quality of big data system.

Methodology/Design: This study is based on primary data that were collected through an online questionnaire survey from large manufacturing firms operating in UAE. Out of total distributed 421 samples, 327 samples were used for final data analysis. The survey was conducted from March-April 2020 and data analysis was done via Structural Equation Modelling (SEM-PLS).

Findings: It emerges that big data analysis (BDA), traditional marketing analysis (TMA) and big data system quality (BDSQ) are significant determinants of new product development (NPD) success. Meanwhile, the BDA and TMA significantly affect the BDSQ. Results of the mediating role of BDSQ in the relationship between the BDA and NPD as well as TMA and NPD are significant.

Implications: There are significant policy implications for practitioners and researchers concerning the role of analytics, particularly big data analytics and big data system quality, when attempting to achieve success in developing new products.

Originality/Value: This is an original study based on primary data from UAE.

Keyword: *Traditional Marketing; Big Data Analytics; Big Data System Quality; New product development; UAE*

1. Introduction

In recent years, the utilization of external knowledge into the organizations analytical approaches has become significant for businesses new product development (Chuang and Lin 2015; Lichtenthaler 2016). In the current era of technology and innovation many academics, scholars and experts urge for much more lively contribution of traditional marketing analytics, big data analytics in new product development (NPD) than is perceived with traditional market studies (Xu et al., 2016). Most traditional marketing strategies are based on the concept of analytics, which deal with small sets of data such as kilobytes, gigabytes, or megabytes. These datasets have limited implementation capacity and analytic platforms, which are available on a researcher's or manager's computer. It cannot be imitated easily and making decisions is done by the central entity. Recent and rapid advances in information technology and marketing have resulted in better mobility, improved solutions, and magnitude for assessing the level of success in new product development (NPD) and strategic activities. Millions of real time points of data have been analysed by Netflix, which supports the company in determining the success of a new show through a pilot.

The data sets, which are complex, unstructured, and large, are referred to as big data which can make and discover the importance of business via its exceptional projecting and analytical competences (Sun, Cegielski, & Li, 2015). From an alternate point of view, Orenaga-Roglá and

Chalmers (2016) explain big data as the current capacity to have a huge measure of information and make inference about different cycles of the organization and client and their connections. There are a lot of opportunities for businesses to involve with clients in terms of analysing, storing and trading huge amount of client insight through big data approaches because of these abilities (Kunz et al., 2017). Commonly, these are in the form of exabytes or terabytes. For instance, genome-analysis, sensor, smartphone apps, social media, and gadgets-based data on the internet require the latest technologies for sourcing, storing, analysing, visualising, and managing data (Xu et al., 2016). More than 500 terabytes of data are hosted by Facebook every day incorporating the posts of users, likes and photos/videos, which are continually being uploaded (Venkatasawmy, 2018). Big data is not just linked with EB (Exabyte), PB (Petabyte), TB (Terabyte), or MB (Megabyte); it is also based on specific data insights, which can help deal with the data affordably.

In marketing, big data analysis (BDA) is different from traditional marketing analysis (TMA) (Xu, 2016). The difference is in terms of 'revolution' instead of 'evolution' of channels of communication. BDA is used by businesses to follow the information flow and analyse large amounts of real time data. In contrast, the focus of TMA is on enhancing the key performance indicators for improved insights about the pricing, advertising, NPD and customer relationship management (Xu, 2016). There is limited research available on analysing the use and effects of BDA because it is a relatively new concept. BDA is used by most organisations so that they can better understand their customers and achieve greater levels of customer engagement (Lai et al., 2018). Irrespective of how it is used, big data is not a solution but instead a raw material. It is still a challenge to transform the data into something that managers can use to develop insights for solving issues and improving performance. There is difference between BDA and TMA based on the four "Vs" (velocity, veracity, variety, and volume) related to data. Making decisions in business could be improved by BDA for better success in NPD.

The focus of RBV is on the association between the success of a product and capabilities/resources (Yu & Yang, 2016). The theoretical underpinning in RBV is the dependence of a firm's performance on the qualities/attributes of its resources and capabilities (Loon, 2016). The resources need to be rare, valuable, non-substitutable, and not able to be copied by rival businesses. The great potential, uncopiable, rare, non-substitutable components are created by the V components. Firms are allowed by RIN (Renewable Identification Numbers) to get more value. Two critical points were put forward by Kaufman (2015) based on the qualities of resources. Firstly, it is important to know about the qualities of resources, which determine why some firms succeed and others do not. Secondly, it is crucial to analyse the way in which companies can improve their sustainable performance. It has been suggested by RBV (Research-Based Value) that a firm has high performance potential when it develops different quality or types of resources to generate specific value through resource complementarities, investments, and complex systems (Venkatasawmy, 2018). The attributes of BDA are distinctive and they include information and system quality. These attributes increase productivity in terms of inventory and logistics management, setting price at the desired or most realistic level and demand/supply management (Venkatasawmy, 2018). BDA competence is achieved through qualities of information and system for improving the performance of a firm (FPER). The important roles of such attributes are highlighted by RBV to achieve a competitive edge (Akter et al., 2016). It is a central tenet of RBV that the profit returns made possible by a firm's strategy are based on the capabilities and resources of that firm.

Though this research area has attracted attention from academics in the present literature (see for instance, Xu et al., 2016; Zhang et al., 2018), most of studies examine big data in relative to corporate development and client retention (Flint, 2002), functionality, quality, colour, prestige and innovativeness linked with a product or brand (Wong & Tong, 2012), pharmaceutical flow properties (Megarry et al., 2019), the association between big data and new product revenue (Johnson et al., 2017), big data in retailing (Bradlow et al., 2017) and so on. Unfortunately, there is limited studies conducted on this subject in terms of examining the impacts of traditional marketing analytics and big data analytics on the success of a new product development, especially in the perspective of United Arab Emirates (UAE). Therefore, this study aims to fill up this gap and also evaluates the effects of mediating role of big data system quality (BDSQ) on the success of a new product.

This study is very important for the managers and researchers to understand the role of analytics, mainly traditional and big data analytics and the mediating role of big data system quality, when attempting to attain success in developing new products. Businesses are mindful of the ways in which knowledge is obtained nowadays, which has been changing dramatically in recent decades. As companies strive to develop new products to meet the ever-changing needs of their target consumers, the question of whether or not such strategic efforts would be successful persists, entailing the need for appropriate methods to address the problem. Moreover, when better marketing techniques and analytic tools work collectively to generate brand value and profitability, this research will help to develop a preliminary understanding of how each of the analytical methods differs from the others in terms of market and strategic organizational requirements. The marketing research and academia will get ideas how to reveal the interconnectedness between TMA, BDA and BDSQ analytic tools and new product success which per se explains how an organization senses and responds speedily to opportunities for innovation in the competitive marketing environment. At the same time, the outcomes of this research are anticipated to provide insights to managers of manufacturing companies in making better decisions that enhance product success which entails providing personalised services to customers thus helping the business to achieve targets and competitiveness.

2. Literature Review and Hypothesis Development

Clearly in these days, there are many items introduced into the market. For that reason, it's no astonishing that New Product Development (NPD) is related to many factors that either make it success or fail such as corporate development and client retention (Flint, 2002), functionality, quality, colour, prestige and innovativeness linked with a product or brand (Wong & Tong, 2012), big data in relative to pharmaceutical flow properties (Megarry, et al 2019), the association between big data and new product revenue (Johnson, et al 2017), big data in retailing (Bradlow et al 2017) but not many studies have look at the type of analytical methods used by companies thus depicting scarcity in the literature. Xu et al (2016) was first study that examined into this phenomenon by utilizing knowledge fusion taxonomy to recognize the connections between traditional marketing analytics (TMA), big data analytics (BDA), and new product success (NPS). Thus, our study aims to expand the dimensions and look into the mediating role of big data quality systems in determining product development success thus filling this aspect in the literature gap.

Initially, the internet was not used by consumers during the web 1.0 and 2.0 eras. There is less complexity in NPD analysis when compared with the current era of web 3.0. Here the regression modelling processes of stochastic, modelling diffusion, multidimensional/mapping

and optimization were analytical methods of marketing, and they proved to be useful. Profit increase, reduced costs, and good performance were enjoyed by firms that employed these analytic marketing tools (Lunardi et al., 2014). The basic tool of analysis used by 70% of the retailers was the spreadsheet. It was argued by Wang et al. (2018) that the potential benefits of using customer analytics are ignored by small retailers. Useful business insights can be provided for NPD through customer surveys, SWOT analysis, and NPV models in some circumstances (Dinçer et al., 2019). There is a need for huge data from different sources for NPD so that the demands of customers and future markets and/or industries can be understood. These are factors of business which are moving and changing rapidly.

Generally, NPD is positively influenced by TMA. It was suggested by Mousavi et al. (2013) that the revenue forecasts, profit projections, cost estimates, and assessment of risks are included in NPD. Moreover, it includes the issue of sales cannibalisation without considering it fatal to another product. Moreover, it is necessary for a firm to consider the information speed and its dissemination, technological change, demand elasticity, and aggregation of forecasts for products related to NPD (Neto & Junior, 2008). Akter et al. (2016) contended that firms performing well use the latest technologies of BDA. BDA provides firms with the methods for developing products in the web 3.0 era, and these are products that consumers want. It is challenging to understand changing tastes in the consumer and marketing environment because they are rapid (Ottman, 2017). New insights into products, competitors, markets, and consumers are provided by BDA in real time. Information may become unreliable for decision-making in NPD due to biased samples and sales estimation in TMA. The use of BDA for real time data can enhance business decisions compared with TMA because the former has the power to deal with uncertainties in real time (Yu & Yang, 2016).

Business intelligence offers several benefits to operational plans. Competitors can be monitored closely, consumers can be observed, and low-cost survey research can be conducted by firms through the use of BDA. Moreover, internet research can be carried out, prototypes can be tested and feedback on them received. For years, businesses have done generally done things repetitively or routinely (Furtado et al., 2017). Cost reductions and improvement in performance are supported by big data. The new designs and responses of consumers to competitors are a key function of business intelligence. Moreover, the key features of a competitor's products, customer feedback and pricing strategies can be learnt by firms using big data (Waller & Fawcett, 2013).

The perfectionist firms depending on TMA and showing ignorance for BDA revolution but the explorer firms using BDA and performing better than TMA (Hazen et al., 2014). The reliability of TMA for creating propositional statements means that firms can depend on TMA for answering queries and finding appropriate solutions for a specific problem. The use of real time big data to date has not been efficient. The uncertainty brought about by real events in blogs, social media, and smartphone apps is missed by TMA. This influences the customisation of knowledge and its accuracy. Conversely, the use of BDA attributes at extreme levels such as strong forecasting tools results in greater success in NPD and automated knowledge (Schoenherr & Speier-Pero, 2015). The matrix defines those firms resisting analytics as bystanders. The dependence of these firms (with low DBA and TMA level) is a heuristic judgment for the manager to make decision about new product development and marketing strategy. For these firms, the complexity in making a decision is low. Practically, these firms depend on the experience and informal knowledge of the managers who are making decisions (Landström, 1998). With this in mind, the quality of decision-making is influenced by the mind-set, knowledge of the manager, storage of information, and environment.

The individual judgment and novelty can influence decision-making in specific situations (Wang et al., 2016). This style becomes suitable for managing social relations but less suitable for digital information management. The level of fusion of knowledge is expected to be poor due to collaborative knowledge between applied sciences and the social sciences not being explored to any great depth. Contradictory results may occur in the knowledge emerging from NPD practice, TMA, and BDA. Consequently, managers make decisions based on a heuristic approach. The level of success in NPD is low because BDA and TMA are poorly used. The following hypotheses are suggested by this discussion:

H1: TMA has a significant impact on the NPD

H2: BDA has a significant impact on the NPD

Moreover, it is a key challenge for most businesses in NPD to extract relevant information for realising a new movie, game or an electronic device. This is because of the rapid diffusion of information and the scale on which this occurs. The data quality problem in the context of supply chain management (SCM) is shown by Hazen et al. (2014), which also can be valid in the development of new products based on information taking from social media.

Many tweets can be extracted through Twitter API with embedded sentiments in them. It shows a marked improvement in contrast to labelling data by hand, which is too time-consuming (Schoenherr & Speier-Pero, 2015). A number of web resources can be searched by managers to forecast the value and recognition of different companies from the social perspective. It was noted by Wamba et al. (2015) that measurement and analysis of viewers regarding a movie on Wikipedia can help to assess its popularity before it is released. Firms are provided with a way to make better strategic decisions and generate success in NPD through data fusion from social media sites and TMA.

A study was conducted by Douglas (2014) on computerisation in the retail industry and how it affected performance. It was found that the quality of information has a positive relationship when the workplace environment is also of high quality. In the similar way, it was identified by Paul et al. (2018) that there is a positive association between quality of information and organisational performance. It was argued by Davis (2014) that the relationship between organisational impact and quality of systems in place is mediated by the quality of information. A positive association was found between the quality of information and that of the system, as well as the quality of information and organisational impact. The direct relationship between organisational impact and quality of system was found to be insignificant. Kaufman (2015) discovered that the quality of the system is a crucial determinant of successful ERP implementation, which must be managed appropriately to achieve a competitive advantage using ERP projects. Other research reported that there is a strong association between quality of information, business performance and business value (Ottman, 2017). It was posited by the RBV perspective that big data analytics outcomes of an organisation are based on the quality of resources that are unique in the market. Heterogeneous resources and how they are linked are taken into account, for instance quality of information and system for analysing how to achieve a competitive edge.

The heterogeneous resources and their connections in the environment of big data have considerable importance. It was stated by Ren et al. (2017) that there were minimal gains in terms of performance outcomes. This was because there is a stubborn disconnection between

the systems in place and how frontline managers and companies make decisions. Operations become complex because of new demands for management of data. Researchers have argued that the quality of technology reflects the level of quality of information in a big data environment. BDA aims to create a viable information ecosystem that can support the sharing of information, decisions, communicated results, and generation of business and managerial insights (Ji-fan Ren et al., 2017). With the use of big data by more firms, the development of a high quality system may become a competitive resource for improving the quality of information.

For effective decision-making, the quality of information is a good foundation. However, there is little information available on the influence of quality of a system on the quality of information. The variation in performance of a system cannot be explained by an IT resource when it is not rare or cannot be copied (Popović et al., 2018). The IT resource in this context is referred to as the BDA's system quality. For instance, the company Netflix's system of movie recommendation or Amazon's dynamic pricing are good examples. The technical aspects of the platform of analytics are determined by system quality. These are specific to a firm and developed over time and they are aspects that cannot be imitated easily.

It has been identified by reviewing the literature on BDA that there are five sets of qualities, namely adaptability of system, integration, response time, accessibility, and privacy. These qualities are important for the provision of solid insights (Gunasekaran et al., 2017). In the model, these dimensions of quality are considered the basic elements of system that is able to forecast the performance of a firm (FPER) and business value (BVAL). The reliability of a system is reinforcing the belief that an analytics platform is free of interference and disruption, and therefore useful to managers. The level of analytics platform to be adopted for fulfilling different needs in dynamic situations is referred to as the adaptability of a system. The integration of a system means its ability to integrate different types of data such as voice, transaction, video, and clickstream (Akter et al., 2016).

The accessibility of a system determines the level to which managers can access an analytics platform with ensured scalability and convenience. Further, the response time of a system determines the responsiveness and timeliness of an analytics platform (Basheer et al., 2018). The privacy of a system refers to the level of security an analytics platform has. This ensures confidentiality of private information (Hazen et al., 2014). The quality of a system is the core of BDA and its characteristics play the key role in business value creation. It has been proposed that the system quality in the BDA environment influences the relationship between product success and business value (BVAL). Therefore, the following hypotheses are considered:

- H3: TMA has a significant impact on the BDSQ
- H4: BDA has a significant impact on the BDSQ
- H5: BDSQ has a significant impact on the NPD.
- H6: BDSQ mediates the relationship between the TMA and NPD.
- H7: BDSQ mediates the relationship between the BDA and NPD.

3. Methodology

This study collected primary data based on an online questionnaire survey sent to large manufacturing firms in UAE. The study is carried out in the manufacturing industry of UAE, because UAE is now of the world's premier business hubs and major consumer and beneficiary of big data (De Mauro et al, 2018) and the manufacturing sector is now one of the biggest

economic sectors in UAE and only large firms have the ability to use big data (Sivarajah et al., 2017). Big investments need to be made in developing big data analysis capabilities (BDAC), which is something that only large organisations can do.

The study is limited only to the manufacturing firms in UAE which is our target population and only the respondents who work under manufacturing firms in the UAE were contacted via e-mail. The email contained the study title, rationale and goal of the study, and all other relevant details to build trust with the respondents. The email also contained a hyperlink that allowed individuals in the research sample to access the survey and then directly respond to it online without the intervention of the researcher, thereby enhancing objectivity and neutrality. The questionnaire was sent during March-April 2020.

During the data collection process, 421 samples were obtained and of these 327 were usable for further data analysis, and subsequently the remainder were discarded because they were incomplete. Thus, a 77.4% response rate was found, which is adequate and in line with Sekaran and Bougie's (2003) suggested response rate for a survey, i.e. 30%.

The data were analysed based on SEM-PLS by using Smart PLS 3.0. This study developed the framework and model based on Ringle et al. (2014). The SEM-PLS technique is a two-step analytical procedure (Hair et al., 2014). The first stage is the measurement model (including the reliability and validity test) and the second stage is the structural model (hypothesis testing).

4.0 Results and Analysis

The initial assessment was conducted with the measurement model to check reliability, dimensionality and validity of the latent constructs using confirmatory factor analysis (CFA). The Cronbach's alpha (α) coefficient is recommended for assessing the reliability. Peterson and Kim (2013) have recommended the composite reliability (CR) test. There are two types of approaches for checking the validity of latent constructs, namely convergent and discriminant validity.

For the measurement model (Figure 1), convergent validity can be ascertained through computing the values for composite reliability (CR), factor loadings and average variance extracted (AVE) (Hair et al., 2014). According to Chin (1998), the factor loadings must be equal to or above 0.70, and the results for factor loadings in this research emerged as consistent with the threshold level, i.e. above 0.70. Thus adequate convergent validity was indicated (Table 1).

Figure 1: Measurement Model

Table 1: Value of Outer Loadings

Another way of checking the convergent validity is by observing AVE, following the Fornell and Larcker (1981) criterion, which requires the AVE values to exceed 0.50. The value for AVE explains the amount of variance captured by a construct, as compared to variance due to measurement error. The composite reliability (CR) shows the extent that the indicator of the construct represents its latent construct. Therefore, the values for CR were found to be greater than 0.70, which is in line with the level suggested by Hair et al. (2014).

Table 2: Reliability and AVE

The Fornell and Larcker (1981) criterion served to establish the discriminant validity of the measurement model. Discriminant validity highlights the extent to which items reflect the difference among measures or constructs, i.e. whether the concepts are distinct. Discriminant validity can be measured by observing the correlation among the constructs' measures, which may potentially overlap. The average amount of variance shared among constructs and their measures must exceed the shared variance among a particular construct and the other model constructs (Basheer et al., 2019). The AVE square roots are presented in Table 3, where the diagonal positions in bold value were found to be greater in value compared to the corresponding column and row values.

Table 3: Discriminant Validity

The indicators' cross-loadings are also observed for measuring the discriminant validity of the constructs. For this purpose, the outer loadings of the indicators for their respective constructs are compared, which are required to exceed their loadings on other model constructs (Junoha et al., 2019). Thus, higher loadings were obtained for all indicators when loaded on their respective constructs. They have lower loadings in the case of other constructs, as shown in Table 1, which validates the constructs having adequate discriminant validity.

Once the reliability and validity analysis are performed for the measurement model, the proposed hypotheses were estimated employing the structural model (Figure 2). The hypotheses were tested through the bootstrapping method, by including 5000 trials (Hair et al., 2014). The path coefficients from the direct paths relationships show that all the hypotheses are significant at the 1% level (p-value <0.000) (Table 4). Similar findings also shown by the moderating path coefficient are also significant at the 1% level (p-value <0.000) (Table 5).

Figure 2: Structural Model

Table 4: Direct results

Table 5: Mediating role of BDSQ

Coefficient of determination (R^2) and Stone-Geisser's (Q^2) are the important criteria used for estimating the structural model. According to Ringle et al. (2014) the coefficient of determination gives the percentage of variance in endogenous latent variable that is explained by the exogenous latent variables. It also reflects the quality of those variables that were added in the model (Hair et al., 2014).

Apart from assessing the explained variance in the model's dependent variable to assess the predictive accuracy of the model (R^2), Stone-Geisser's (Q^2) test must be employed for estimating the model's predictive relevance (Hair et al., 2014). For calculating Q^2 value, a blindfolding procedure was performed in Smart-PLS, which makes it possible to re-estimate the model (Chin, 1998). It is generally performed for the model's endogenous reflective latent variable by assuming that it may have some predictive relevance, which turns out to be true if $Q^2 > 0$ for the endogenous latent construct. Here the R^2 value is obtained through the measurement model (Figure 1) and Q^2 value is obtained through the blindfolding procedure mapped in Figure 3. The R^2 and Q^2 values are shown in Table 6, which indicates the model has a good fit.

Figure 3: Blindfolding

Table 6: Value of Q^2 and R^2

5. Discussion

The current paper makes an important theoretical contribution to the topic by showing evidence for the impact of traditional data analytics and big data analytics and the mediating role of big data quality systems in new product success. Yaqoob et al. (2016) have called for more research in the area of big data; subsequently, the present study fills this gap by devising a framework for explaining this phenomenon. Results for the hypotheses indicate that for all of them, there is a significant association among their endogenous latent constructs. The findings indicate that the BDA, TMA and BDSQ are significant determinants of the success in NPD. Meanwhile, the BDA and TMA significantly affect the BDSQ. As well, the results for the mediating role of BDSQ in the relationship between the BDA and NPD as well as TMA and NPD (H6-H7) are significant. They agree with the findings of Xu et al. (2016) who confirm that firms adopting both a high level of TMA and BDA have the greatest success in NPD.

The success in NPD has depends on the mechanism of knowledge discovery from social media. In a practical sense knowledge exists without semantic information and structure but it does generate valuable insights. Firms need to combine TDA and BDA if they are to succeed in the market. This is done to generate knowledge and information that gives them a competitive advantage, which are crucial for the success in NPD. Specifically, for increasing the success in NPD, firms can customise their new products/services. It emerges that information and system quality are two crucial determinants of value and new product performance driven by IT (Information Technology). In general, TMA and BDA positively impact on the success of NPD which is in line with Cravens and Piercy (2005). Additionally, an organisation needs to take into account the pace of technological change, speed of data dispersal, variety of demand, and families of products concerning NPD (Herbig et al., 1994).

On the other hand, success in launching a new product involves a great deal of information from various sources and stakeholders (Xu et al., 2016). Moreover, big data enables firms to identify previously unrecognised needs of their customers. New product success needs to the proper organisation of information and input from various investors. As the pace of change in technology, markets, competition, regulations, and inputs increases and as more of these factors become significant for a specific product, the complexity and speed with which a firm acquires and analyses information must also accelerate. In passive markets, TMA may still work fine for NPD. Nevertheless, some markets may need information from social media, while others may need less traditional data, and the greater quantity of digital data is contingent on the pace with which each main factor changes. This is to say that not all the products that are launched in the market will succeed. New product success is determined by several other factors such as sales revenue, word-of-mouth support, profits, customer retention and corporate growth. The key features involved in new product success are technology, functionality, innovativeness, higher speed to market, entry regulations, product quality and good branding. However, in this age it is the big data that can be decisive for new product success (Hajli et al., 2020).

In terms of practical implications, the results provide insights to managers by showing how the combination of TDA and BDA tools are directly linked to new product success and the mediating role of big data quality systems. Our findings reveal the effective use of quality data systems to devise products which can clarify how managers and their firms understand and

reply quickly the demands for innovation in the digital age. The first step should be to understand quality requirements for both big data systems and engineering processes in general. Consequently, this step may help address both big data characteristics and quality requirements more systematically, which in turn, can reduce the number of missing quality requirements while accounting for big data characteristics. Therefore, the taxonomy of this study recommends that all businesses will benefit from using both TMA and BDA. However, possibly not all circumstances validate the cost of analysing and collecting both types of data. The study assumes that managers can utilise each or both kinds of data. Additionally, the taxonomy and proposals offer an avenue for academics to examine the value of each category of data analytics compared to the other in terms of product development strategic needs.

The theoretical contributions of this study are of two kinds. Firstly, it finds there is a direct and positive relationship between TMA and BGA which both impact on NPD, thus demonstrating how combining the two can only be positive for companies. It enables capabilities for co-innovation and new product development. This is in line with the findings of Cravens and Piercy (2005) so this embryonic research topic can be explored more fully. Secondly, the study is the first to empirically test a framework that seeks to explain the impact of TDA and BDA in new product success with the mediating role of BDASQ.

This research has some implications for managers and especially in their role of developing and overseeing new product development successfully. Manufacturing companies should nurture valuable organisation-wide BDAC by training staff or hiring outside experts or specialists, where knowledge and good practices can be shared, and endorsing the circulation of an evidence-based and business data-driven ethos (Mikalef et al., 2019). It means appointing alert and forward-thinking supervisors or leaders who understand the relevant activities and procedures, IT infrastructure and can work with Chief Information Officers, relevant staff, etc. (Barton & Court, 2012).

6. Conclusion

There are many internal and external elements which make it challenging for companies to deal with clients' ever-changing wants and needs. A significant amount of information is required from various stakeholders for a new product to succeed. This study investigated the impact of traditional marketing analytics and big data analytics on the success of a new product. Additionally, the study examined the mediating effects of the role of big data system quality. The results of the study show that the BDA, TMA and BDSQ are significant determinants of the success in NPD. With technology, markets, competition, regulations, and inputs changing all the time, the speed and complexity with which the information is acquired and analysed by a firm accelerates as well. TMA can work better for NPD in docile markets. There is need for information from social media for some industries or markets. The change of speed with which important elements alter the market is due to the amount of digital information. A framework has been provided here for future research to build on. Real time information can be extracted by company managers to understand what people want in terms of products.

This study recommends that all businesses and organizations will benefit from the adoption of a high level of TMA, BDA and BDSQ to have a great success in NPD. Nevertheless, feasibly not all circumstances validate the cost of utilizing all these methods at once. The study bids understanding for managers and relevant bodies to support regulate when to practice each or every kind of analytics. In addition, the study implication and suggestions

offer a preliminary idea for other examiners to explore the importance of each of the forms of information analytics in comparison to others with regards to businesses and organization strategic requirements. Similarly, impending studies ought to exam the suggestions to determine if a variance actually exists in desired NPD of companies that are following the projected approaches or if companies really are in need of the recommended analytical methods.

This study will be significant for policy makers, practitioners and researchers regarding the role of analytics, mainly big data analytics and big data system quality, when endeavouring to attain success in developing new products. For that reason, companies are aware of the way in which information is acquired which has been transformed permanently. This same reason can be seen by the advent of social media and how it is now so consumer-based. Social media has changed the way in which people communicate with each other, talk about products, and make purchases. Disciplines including multimedia management, analytics of social media, network analysis, opinion mining, and trend discovery are combined to help analyse and make sense of social data. Good marketing strategies and analytic tools work collectively to create value. For instance, the focus of firms is on the way in which success in NPD is influenced by advertising. In the era of social media, people are influenced by the purchasing behaviours of their friends. People's purchasing decisions are based on how products are perceived and reviewed. So here the mining of text and sentiment are crucial aspects of BDA.

Finally, there are certain limitations evident in this study. It covered only the manufacturing firms in UAE so the findings cannot be generalised to other sectors and locations. To overcome this limitation, future researchers could apply a similar model to other industries and countries to cross-validate and generalise their findings.

References

- Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., and Childe, S. J. (2016), "*How to improve firm performance using big data analytics capability and business strategy alignment?*" International Journal of Production Economics, 182, 113-131.
- Barton, D. and Court, D. (2012), "*Making Advanced Analytics Work for You*", Harvard Business Review, 90 (10), 78-83.
- Basheer, M. F., Hafeez, M. H., Hassan, S. G., and Haroon, U. (2018), "*Exploring the role of TQM and supply chain practices for firm supply performance in the presence of organizational learning capabilities: a case of textile firms in Pakistan*" Paradigms, 12(2), 172-178.
- Basheer, M., Siam, M., Awn, A., and Hassan, S. (2019). "Exploring the role of TQM and supply chain practices for firm supply performance in the presence of information technology capabilities and supply chain technology adoption: A case of textile firms in Pakistan", *Uncertain Supply Chain Management*, Vol. 7, No. 2, pp. 275-288.
- Bradlow, E. T., Gangwar, M., Kopalle, P., and Voleti, S. (2017), "*The role of big data and predictive analytics in retailing*". Journal of Retailing, 93(1), 79-95.
- Chin, W. W. (1998), "*The partial least squares approach to structural equation modelling*". Modern Methods for Business Research, 295(2), 295-336.
- Chuang, S. H., and Lin, H. N. (2015), "*Co-creating e-service innovations: Theory, practice, and impact on firm performance*". International Journal of Information Management, 35(3), 277-291.

- Cravens, D. W., and Piercy, N. F. (2005), "In T. Emrich (Ed.)", Strategic marketing Higher Education. Veracity in big data reliability of routes. Boston: McGraw-Hill Irwin.
- Davis, C. K. (2014), "*Beyond data and analysis*". Communications of the ACM, 57(6), 39-41.
- De Mauro, A., Greco, M., Grimaldi, M., and Ritala, P. (2018), "*Human resources for Big Data professions: A systematic classification of job roles and required skill sets*". Information Processing & Management, 54(5), 807-817.
- Dinçer, H., Yüksel, S., and Martinez, L. (2019), "*Balanced scorecard-based Analysis about European Energy Investment Policies: A hybrid hesitant fuzzy decision-making approach with Quality Function Deployment*". Expert Systems with Applications, 115, 152-171.
- Douglas, K. (2014), "*How data is changing our world*". Nurse Leader, 12(5), 37-67.
- Flint, D. J. (2002), "*Compressing new product success-to-success cycle time: Deep customer value understanding and idea generation*". Industrial marketing management, 31(4), 305-315.
- Fornell, C., and Larcker, D. F. (1981), "Structural equation models with unobservable variables and measurement error: Algebra and statistics". Los Angeles, CA: SAGE Publications.
- Furtado, L., Dutra, M., and Macedo, D. (2017), "*Value creation in big data scenarios: A literature survey*". Journal of Industrial Integration and Management, 2(01), 1750002.
- Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., Childe, S. J., Hazen, B., and Akter, S. (2017), "*Big data and predictive analytics for supply chain and organizational performance*". Journal of Business Research, 70, 308-317.
- Hair Jr, J. F., Sarstedt, M., Hopkins, L., and Kuppelwieser, V. G. (2014), "*An emerging tool in business research*". European Business Review, 26(2), 106-121.
- Hajli, N., Tajvidi, M., Gbadamosi, A., and Nadeem, W. (2020), "*Understanding market agility for new product success with big data analytics*". Industrial Marketing Management, 86, 135-143.
- Hazen, B. T., Boone, C. A., Ezell, J. D., and Jones-Farmer, L. A. (2014), "*Data quality for data science, predictive analytics, and big data in supply chain management: An introduction to the problem and suggestions for research and applications*". International Journal of Production Economics, 154, 72-80.
- Herbig, P., Milewicz, J., and Golden, J. E. (1994), "*Differences in forecasting behavior between industrial product firms and consumer product firms*". Journal of Business & Industrial Marketing, 9(1), 60-69
- Ji-fan Ren, S., Fosso Wamba, S., Akter, S., Dubey, R., and Childe, S. J. (2017), "*Modelling quality dynamics, business value and firm performance in a big data analytics environment*". International Journal of Production Research, 55(17), 5011-5026.
- Johnson, J. S., Friend, S. B., and Lee, H. S. (2017), "*Big data facilitation, utilization, and monetization: Exploring the 3Vs in a new product development process*". Journal of Product Innovation Management, 34(5), 640-658.
- Junoha, M.Z.B.H.J.M., bin Hidhiir, M.H., and Basheer, M.F. (2019), "*Entrepreneurial financial practices in Pakistan: The role of access to finance and financial literacy*". International Journal of Innovation, Creativity and Change, 7(9), 210-231.
- Kaufman, B. E. (2015), "*The RBV theory foundation of strategic HRM: critical flaws, problems for research and practice, and an alternative economics paradigm*". Human Resource Management Journal, 25(4), 516-540.
- Kunz, W., Aksoy, L., Bart, Y., Heinonen, K., Kabadayi, S., Ordenes, F. V., and Theodoulidis, B. (2017), "*Customer engagement in a big data world*". Journal of Services Marketing, 31(2), 161-171.

- Lai, Y., Sun, H., and Ren, J. (2018), "*Understanding the determinants of big data analytics (BDA) adoption in logistics and supply chain management*". The International Journal of Logistics Management, 29(2), 676-703.
- Landström, H. (1998), "*Informal investors as entrepreneurs: Decision-making criteria used by informal investors in their assessment of new investment proposals*". Technovation, 18(5), 321-333.
- Lichtenthaler, U. (2016), "*Determinants of absorptive capacity: The value of technology and market orientation for external knowledge acquisition*". Journal of Business & Industrial Marketing 31 (5), 600-610
- Loon, M. (2016), "*The effects of higher-order thinking dispositions, job-related learning and creativity on innovation behaviour*". (Doctoral dissertation, University of Newcastle, Australia)
- Lunardi, G. L., Becker, J. L., Maçada, A. C. G., and Dolci, P. C. (2014), "*The impact of adopting IT governance on financial performance: An empirical analysis among Brazilian firms*". International Journal of Accounting Information Systems, 15(1), 66-81.
- Megarry, Andrew J., Sadie ME Swainson, Ron J. Roberts, and Gavin K. Reynolds (2019), "*A big data approach to pharmaceutical flow properties*". International journal of pharmaceutics 555: 337-345.
- Mikalef, P., Boura, M., Lekakos, G., and Krogstie, J. (2019), "*Big data analytics capabilities and innovation: the mediating role of dynamic capabilities and moderating effect of the environment*". British Journal of Management, 30(2), 272-298.
- Mousavi, S. M., Tavakkoli-Moghaddam, R., Vahdani, B., Hashemi, H., and Sanjari, M. (2013), "*A new support vector model-based imperialist competitive algorithm for time estimation in new product development projects*". Robotics and Computer-Integrated Manufacturing, 29(1), 157-168.
- Neto, M. V. S., and Junior, J. V. M. (2008), "Afimal, o que é Business Process Management (BPM)? Um novo conceito para um novo context", *Revista Eletrônica de Sistemas de Informação*, Vol 7, No.2, pp. 1-19.
- Orenga-Roglá, S., and Chalmeta, R. (2016), "*Social customer relationship management: Taking advantage of Web 2.0 and Big Data technologies*". SpringerPlus, 5(1), 1462.
- Ottman, J. (2017), "*The new rules of green marketing: Strategies, tools, and inspiration for sustainable branding*". Sheffield, UK: Greenleaf Publishing.
- Paul, P., Aithal, P., and Bhuimali, A. (2018), "*Business Informatics: With Special Reference to Big Data as an emerging Area: A Basic Review*". International Journal on Recent Researches in Science, Engineering & Technology, 6(4), 21-29.
- Peterson, R. A., and Kim, Y. (2013), "*On the relationship between coefficient alpha and composite reliability*". Journal of Applied Psychology, 98(1), 194-198.
- Popovič, A., Hackney, R., Tassabehji, R., and Castelli, M. (2018), "*The impact of big data analytics on firms' high value business performance*". Information Systems Frontiers, 20(2), 209-222.
- Ren, J.-f., Fosso Wamba, S., Akter, S., Dubey, R., and Childe, S. J. (2017), "*Modelling quality dynamics on business value and firm performance in big data analytics environment*". International Journal of Production Research, 55(17), 1-16.
- Ringle, C. M., Wende, S., and Becker, J.-M. (2014), "*SmartPLS 3. Hamburg: SmartPLS*". Academy of Management Review, 9, 419-445.
- Schoenherr, T., and Speier-Pero, C. (2015), "*Data science, predictive analytics, and big data in supply chain management: Current state and future potential*". Journal of Business Logistics, 36(1), 120-132.

- Sekaran, U., and Bougie, R. (2003), "Research Methods for Business: A Skill Building Approach", New York: John Wiley & Sons.
- Sivarajah, U., Kamal, M. M., Irani, Z., and Weerakkody, V. (2017), "*Critical analysis of Big Data challenges and analytical methods*". Journal of Business Research, 70, 263-286.
- Sun, S., Cegielski, C. G., and Li, Z. (2015), "*Amassing and analyzing customer data in the age of big data: A case study of Haier's Online-to-Offline (O2O) business model*". Journal of Information Technology Case and Application Research, 17(3-4), 156-165.
- Venkatasawmy, R. (2018), "*Communication and Media Education in an Era of Big Data*". Journal of Interdisciplinary Studies in Education, 7(1), 87-101.
- Waller, M. A., and Fawcett, S. E. (2013), "*Data science, predictive analytics, and big data: a revolution that will transform supply chain design and management*". Journal of Business Logistics, 34(2), 77-84.
- Wamba, S. F., Akter, S., Edwards, A., Chopin, G., and Gnanzou, D. (2015), "*How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study*". International Journal of Production Economics, 165, 234-246.
- Wang, G., Gunasekaran, A., Ngai, E. W., and Papadopoulos, T. (2016), "*Big data analytics in logistics and supply chain management: Certain investigations for research and applications*". International Journal of Production Economics, 176, 98-110.
- Wang, Y., Kung, L., and Byrd, T. A. (2018), "*Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations*". Technological Forecasting and Social Change, 126, 3-13.
- Wong, S. K. S., and Tong, C. (2012), "*The influence of market orientation on new product success*". European Journal of Innovation Management 15 (1),99-121
- Xu, Z. (2016), "Three essays on Big Data Analytics, Traditional Marketing Analytics, knowledge discovery, and new product performance". Dissertation. ProQuest Dissertations and Theses.
- Xu, Z., Frankwick, G. L., and Ramirez, E. (2016), "*Effects of big data analytics and traditional marketing analytics on new product success: A knowledge fusion perspective*". Journal of Business Research, 69(5), 1562-1566.
- Yaqoob, I., Hashem, I. A. T., Gani, A., Mokhtar, S., Ahmed, E., Anuar, N. B., and Vasilakos, A. V. (2016). "Big data: From beginning to future", *International Journal of Information Management*, Vol. 36, No. 6, pp. 1231-1247.
- Yu, S., and Yang, D. (2016), "*The Role of Big Data Analysis in New Product Development*". Paper presented at the 2016 International Conference on Network and Information Systems for Computers (ICNISC).
- Zhang, Y., Tan, K. H., Li, Y., and Tse, Y. K. (2018), "*Unlocking the power of big data in new product development*". Annals of Operations Research, 270(1-2), 577-595.

Figures

Figure 1: Measurement model

Figure 2: Structural Model

Figure 3: Blindfolding

Tables

Table 1: Value of Outer Loading

	BDA	BDSQ	NPD	TMA
BDA1	0.918			
BDA2	0.872			
BDA3	0.929			
BDA4	0.907			
BDA5	0.926			
BDSQ1		0.878		
BDSQ2		0.837		
BDSQ3		0.902		
BDSQ4		0.909		
BDSQ5		0.869		
NPD1			0.901	
NPD10			0.906	
NPD2			0.898	
NPD3			0.863	
NPD4			0.882	
NPD5			0.817	
NPD6			0.874	
NPD7			0.844	
NPD9			0.896	
TMA2				0.894
TMA3				0.900
TMA4				0.884
TMA5				0.914
TMA6				0.883
TMA1				0.887

Table 2: Reliability and AVE

	Cronbach's Alpha	rho_A	CR	(AVE)
BDA	0.948	0.950	0.960	0.829
BDSQ	0.926	0.928	0.944	0.773
NPD	0.962	0.964	0.967	0.768
TMA	0.950	0.950	0.960	0.799

Table 3: Discriminant Validity

	BDA	BDSQ	NPD	TMA
BDA	0.901			
BDSQ	0.896	0.879		
NPD	0.672	0.724	0.876	
TMA	0.892	0.710	0.696	0.894

*Bold data indicate the variance extracted for each construct is bigger than its squared correlations with other constructs

Table 4: Path Modelling

	(O)	(M)	(STDEV)	O/STDEV	P Values
BDA -> BDSQ	0.509	0.514	0.093	5.495	0.000
BDA -> NPD	0.368	0.373	0.075	4.934	0.000
BDSQ -> NPD	0.724	0.726	0.066	10.924	0.000
TMA -> BDSQ	0.457	0.451	0.094	4.838	0.000
TMA -> NPD	0.331	0.328	0.076	4.359	0.000

Table 5: Mediating role of BDSQ

	(O)	(M)	(STDEV)	(O/STDEV)	P Values
BDA -> BDSQ -> NPD	0.368	0.373	0.075	4.934	0.000
TMA -> BDSQ -> NPD	0.331	0.328	0.076	4.359	0.000

Table 6: Q² and R²

	SSO	SSE	Q ²	R ²
BDA	1085.000	1085.000		
BDSQ	1085.000	353.340	0.674	0.882
NPD	1953.000	1181.894	0.395	0.524
TMA	1302.000	1302.000		

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