Asia Pacific Journal of Advanced Business and Social Studies
ISBN (eBook): 978 0 9943656 7 5 | ISSN : 2205-6033
Year: 2023, Volume: 8, Issue: 1

INTEGRATION OF BUSINESS ANALYTICS INTO DECISION-MAKING IN PHARMACEUTICAL SALES AND MARKETING: A RESEARCH FRAMEWORK

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Abstract

Traditionally, pharmaceutical sales and marketing depend highly on relationship marketing and subjective or judgment decision-making, which may risk business and public health. There is an urgency for a more reliable decision-making process, such as data-driven decision-making with business analytics, to ensure companies achieve their societal goal of reducing human suffering from illness effectively. Through a systematic literature review, this research assesses the use of business analytics and its integration into sales and marketing decision-making. This research analyses the literature using thematic analysis and a logic model and then proposes a comprehensive framework that integrates business analytics and decision-making process to improve sales performance. Multiple factors or variables are identified to impact business analytics and decision-making, indicating the need to explore the specific context of the pharmaceutical market. This study suggests future studies using a case study approach to understand the pharmaceutical phenomenon better. Further analysis with survey and SEM can be used to confirm relevant factors and the magnitude of the relationship between variables.

Keywords: Big Data Analytics, Business Analytics, Business Analytics Capabilities, Data-Driven Decision-Making, Pharmaceutical Sales & Marketing.

1. Introduction

Traditionally pharmaceutical sales and marketing depend highly on relationships and intuition for sales and marketing decision-making (Matikainen et al., 2017; Saavedra et al., 2017). In such situations, companies may not objectively evaluate the true business potentials using relevant data but instead based on the perceived relationship quality with doctors. Quality of relationship with doctors certainly will impact the number of prescriptions and sales (Sah & Fugh-Berman, 2013; Patwardhan, 2016; Lee & Begley, 2016). However, it is prone to individual bias. Different people may have different perceptions, which translates into different business expectations (Frow et al., 2011; Lee & Begley, 2016).

Several studies have proven that data-driven decision-making (DDDM) is an effective strategy for improving firms' performance in many different industries (Akter et al., 2016; Brynjolfsson & McElheran, 2016; Troisi et al., 2020). The pharmaceutical industry is a data-intensive industry in nature. The amount of data collected and analysed to develop and launch a new drug is abundant, such as from long and massive clinical trials, phase 1, phase 2, and 3 (Handoo et al., 2012). Once the product is ready to be marketed, the company conducts an epidemiology assessment to evaluate the potential business size in a particular market. This process is commonly known as patient flow or patient funnel. Companies also identify potential users and their prescription behaviour through segmentation and targeting exercises (Paich et al., 2009).

Companies spend substantial resources in terms of time, people, and money collecting those data. Often these data sit in different parts of the organisation and are used for specific purposes, and usually are not made readily available to other departments. This phenomenon raises the question of whether all those data are relevant for companies to make better decisions or how the company should collect, manage, analyse and use the data for better decision-making (Sendyona et al., 2016).

2. Literature Review

2.1 Pharmaceutical sales and marketing

Relationship marketing is a vital component of pharmaceutical sales and marketing, but it also presents problems and hazards if not managed appropriately. The capacity to create, maintain, and strengthen customer relationships is critical for business performance. Pharmaceutical corporations place a high value on this element, mainly through the interactions between pharmaceutical sales representatives (PSR) and physicians (Lieb & Scheurich, 2014; Villalba, 2019; Price et al., 2021). Because of technological advancements, businesses may now employ CRM (customer relationship management) solutions for consumer involvement. In a pharmaceutical firm, salespeople describe visits to physicians in CRM software, which are then analysed to influence future engagement actions (Kientop, 2010; Chressanthis et al., 2014; Krizanova et al., 2018). Many, however, have expressed worry about its negative aspects. Pharmaceutical sales and marketing approaches rely on relationship marketing and intensely focus on PSR and physician connections. Because of the emphasis on relations, sales and marketing, investments and activities tend to be subjective and intuition-based. The perception of certain employees, particularly those who engage directly with doctors, has been overrated. Business potential in a specific account, hospital or location is frequently predicted depending on how well the connection with significant prescribers in the area is. The definition of relationship quality varies from person to person, making it unsafe to rely on for an essential business decision. Paich et al. (2009) proposed an integrated system dynamic in the pharmaceutical sector that incorporates patient flow, doctor adoption, and treatment attractiveness to assess the true commercial potential (Paich et al. 2009). Statistics or data like disease prevalence and incidence, doctor segmentation, and other product competitiveness metrics reflect the three factors.

2.2 Data-driven decision-making

The concern is whether pharmaceutical corporations have implemented a culture of data-driven decision-making in their sales and marketing operations. Data-driven decision-making (DDDM) is a method of determining the best option supported by data. Using data is no longer a choice in the age of big data but rather a need (Lu et al., 2019). Some of the most common manifestations of the DDDM include business analytics, data analytics, and big data analytics. Business analytics (BA) is a decision-making tool business use to create answers to current business challenges. BA may be descriptive, predictive, or prescriptive depending on the type of business problem to address and the goal to reach.

A review of past research on DDDM and business analytics or big data analytics reveals a propensity to focus on the perceptions of executives, analysts, IT managers, or salespeople (Akter et al., 2016; Mikalef et al., 2019; Pugna et al., 2019; Suoniemi et al., 2020; Shazbaz et al., 2020; Gupta et al., 2021). This technique does not work in the pharmaceutical sales and marketing context because sales and marketing managers are the primary decision-makers. Business analysts, sometimes known as commercial effectiveness managers, contribute to the analysis and insight development, although their function is primarily supportive. Hence, this study will explore the perception of sales managers, marketing managers and business analysts on DDDM, business analytics and its usage and impact on sales performance.

3. Methodology

We follow the systematic literature review principles suggested by Tranfield et al. (Tranfield et al., 2003), which consists of three main stages, planning, execution and reporting. This approach allows us to review all relevant past studies in business analytics, then help us to identify gaps in the existing studies and position new agendas for future research. The following subsections describe the three stages previously mentioned.

In the planning stage, we developed the protocol for the literature review. The protocol consists of the research question, which guided the selection of papers, the search strategy, the inclusion criteria and the synthesis method. The following research question drives the literature review process: *What are the requirements for effective business analytics in pharmaceutical marketing, and how does business analytics impact sales performance?* This research question covers the factors, variables, or capabilities that may impact business analytics implementation and the process of making an impact, such as through the decision-making process. From this research question, we identified relevant past publications.

In the execution stage, we used Scopus and ScienceDirect as the sources (Lim & Rasul, 2022; Lim et al., 2022). It is very important to identify the relevant keywords for a search string (Lim et al., 2023; Rasul et al., 2020a: Rasul et al., 2020b; Rasul et al. 2023).We wanted to focus our search on the specific area of pharmaceutical marketing. We employed the following search keyword: *"data driven decision making" OR "data driven decision" OR "business analytics" OR "data analytics" OR "big data analytics" AND "performance" OR "firm performance" OR "sales performance" AND "pharmaceutical" AND "marketing" OR "sales*". However, this keyword combination resulted in only four (4) papers. The low number of papers indicates the scarcity of business analytics research in pharmaceutical marketing and sales. Due to the limited results in the pharmaceutical context, we decided to open the search to any industry. The revised search keyword was: *"data driven decision making" OR "data driven decision" OR "business analytics" OR "data analytics" OR "big data analytics" AND "performance" OR "firm performance" OR "sales performance"*. We included 53 articles after implementing inclusion and exclusion, as shown in figure 1.

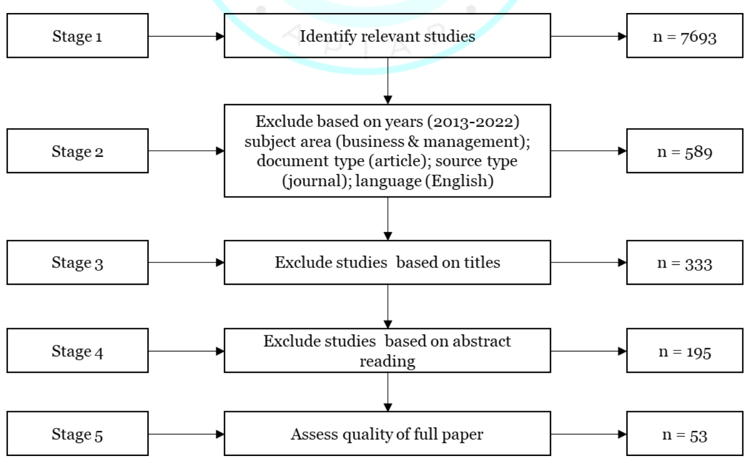

Figure 1. Paper selection process

We used an excel spreadsheet to code the data, where the row represented the article and the columns defined all the factors or variables mentioned in the articles. We recorded all the variables from each study using the original words from the authors. This approach allowed us to map all the factors or variables that authors have explored in the past. The results were represented as a matrix of factors in the 53 articles.

In reporting the findings, we used thematic analysis, descriptive evaluation and logic model as data synthesis methods. The logic model is a sequential staging of factors that show the possible causal relationship between variables. We defined the variables as independent, mediating, moderating and dependent variables. We specifically reviewed the role of decision-making and the integration of business analytics into decision making. The reason is that business analytics is a form of the data-driven decision-making process; hence it is reasonable to evaluate the papers based on their point of view on decision-making (Sahay, 2020).

4. Result and discussion

We included 53 papers published from 2013 to 2022. Figure 2 shows the distribution of papers based on publication year and journal quartile. Around 70% (37) of articles were published in the last five years (2018-2022), with 2018 contributing the most.

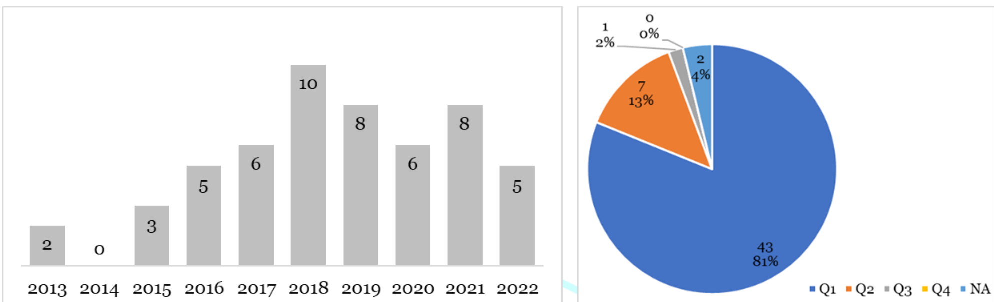

Figure 2. Distribution of paper by publication year & journal quartile

We ensure the quality of papers by including peer-reviewed articles published in reputable journals. 85% (n=45) of the papers are empirical research from many sectors and geographies. The other 15% (n=8) papers are literature reviews and framework development. Figure 3 illustrates the different research methods used by the researcher in past studies.

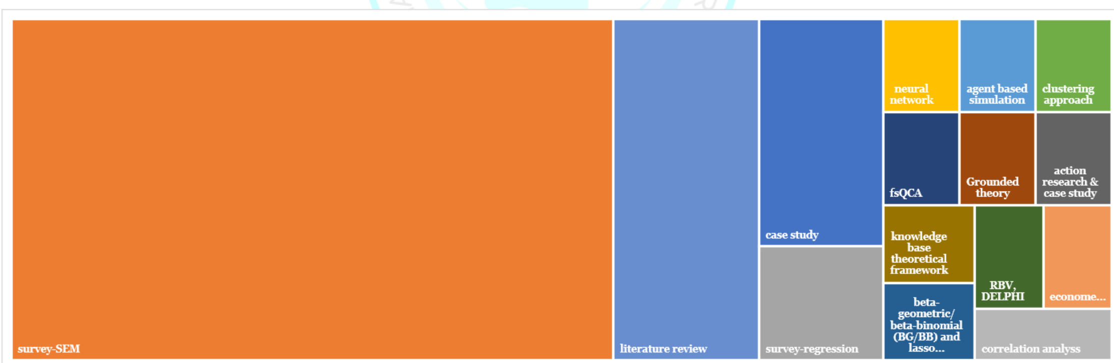

Figure 3. The research method used in past studies

Table 1: Variables mapping

	Variables name	n		Variables name	n
Independent variables	Data quality	17	Dependent variables	Business value/competitive advantage	24
	Technology infrastructure/tools	25		Financial performance	12
	DA/BA/BDA adoption/implementation	18		Process, functional, and operational performance	19
	Technical knowledge/skill	29		New product success	2
	Domain knowledge	2		Decision-making quality	8
	Organisation/culture/structure	13		DA/BA/BDA satisfaction	6
	Management/governance/process	12		Customer value	3
	Leadership	9	Mediating variables	DA/BA/BDA adoption	23
	External factors	6		People capability	4
Moderating variables	DA/BA/BDA	4		Organisation/management capabilities	14
	Organisation/management	6		Decision-making quality	5
	People capability	4		Customer insight	4
	Financial performance	1	n = frequency of appearance		
	Competition	1			

Using the author's own terms, we identified 173 factors or variables related to business analytics. New variables may still emerge as business analytics rapidly evolves, especially in the big data era. As 85% of the papers are empirical research exploring the causal relationship between variables under specific empirical models, we can map the variables into dependent, moderating, mediating and independent variables. Using thematic and descriptive evaluation, we categorise the 173 variables based on the similarity of meaning as intended by the authors. Table 1 shows the categorisation of variables.

Most authors placed data analytic/business analytic/big data analytic (DA/BA/BDA) related variables as either independent or mediating variables toward performance. This approach is aligned with this research objective to understand the impact of business analytics on performance. However, some authors also use DA/BA/BDA-related variables as the dependent variable and moderating variables. In the next section, we will discuss the most common variables identified in the literature.

4.1 Data-driven decision-making and business analytics

Business analytics (BA) is one of the decision-making tools used by companies to generate solutions to existing business problems. The concept was initially introduced in the mid of 1950s. It re-emerges and becomes an important area with the advancement of information technology (IT) and data availability (Cao et al., 2015a;). Sahay (2020) defines business analytics as "*a data-driven decision-making approach that uses statistical and quantitative analysis, information technology, management science (mathematical modelling, simulation), along with data mining and fact-based data to measure past business performance to guide an organisation in business planning and effective decision-making*" (Sahay, 2020).

Holsapple et al. (2014) argue that the fundamental understanding of business analytics shapes how the company implements it. Employees can perceive BA as an evidence-based decision-making movement, practice & technology, a transformation process from data into actions, quantitative capabilities, and a data-driven decision-making paradigm. Those who view BA as a movement and paradigm will value it more than just a tool; hence tends to create an organisational environment to support it. Those who view BA as another tool will evaluate the practical benefits of BA relative to other decision-making or analysis tools (Holsapple et al., 2014). Despite the different points of view on the foundational definition of BA, the implementation is observable in the extent and frequency of usage. Several common approaches are statistical analysis, forecasting, optimisation, simulation & scenario development, KPI dashboard, social media analysis, data visualisation, etc. (Cao et al., 2015b; Cao, Duan, & Cadden, 2019).

4.2 Business Analytics Capability

The research on business analytics and big data analytics is derived from information systems (IS) research. In IS research, it is believed that the value of a business analytics organisation must possess the right level of people capability, technology or infrastructure capability and management capability (Akter et al., 2016; Wamba, 2017; Ji-fan Ren et al., 2017)—the level of professional skills and knowledge possessed by BA staff. People capability refers to the technical skill of analytics professionals (know-how) such as operating systems, statistics, database management, visualisation, etc. (Akter et al., 2016; Wamba, 2017). Not only a clear understanding of the relevant technology and tools but business analysts or employees involved in business analytics must also possess the right level of business knowledge, which refers to the understanding of company strategies and plans; and an understanding of the business environment (Torres et al., 2018). Wamba (2016) suggested that relational knowledge is another essential aspect because business analytics involves sharing information and influencing others. Business analytics activities generate insight to be taken into consideration for decision-making. Analysts are often not the decision-makers. Hence their ability to communicate their insights and convince decision-makers are equally important as the analytics itself (Wamba, 2017).

Technology or infrastructure capability refers to system connectivity, compatibility and modularity. Ideally, the analytics system should be connected across different functions and locations. The system includes the application, hardware, data and network. By being connected across roles and places, the system allows rapid development and deployment of analytics. Compatibility means the ability of the system to facilitate the continuous flow of information for real-time decision-making (Akter et al., 2016; Wamba, 2017; Ji-fan Ren et al., 2017). It also refers to how easy to use the system across different analytic platforms and organisations regardless of location. The infrastructure must also have the ability to integrate data from disparate sources. The data should be available regarding sufficiency and validity (Torres et al., 2018).

Management capability is handling routines in a structured (rather than ad hoc) manner to manage IT resources following business needs and priorities. The first element is planning, identifying business opportunities and how BA can improve performance. The second element is an investment decision, reflecting a BA investment's cost and benefit analysis. Thirdly, coordination is the routine capability that structures the cross-functional synchronisation of analytics activities. Fourthly, controlling ensures proper commitment and utilisation of resources, including budget and human resources. The last element is the top management's vision, strategy, beliefs and influence on opportunities related to BA (Akter et al., 2016; Wamba, 2017; Ji-fan Ren et al., 2017; Torres et al., 2018; Gunasekaran et al., 2018; Ren et al., 2019).

4.3 Decision-making quality & efficiency

Two aspects of decision-making are being considered, quality and efficiency. Decision-making quality refers to decision outcomes that are accurate, correct, precise, flawless, error-free and reliable (Ghasemaghaei et al., 2018; Ghasemaghaei, 2019; S. Shamim et al., 2019). Quality decision-making also means a better understanding of customers (Cao et al., 2015a; Wang & Byrd, 2017; Cao, Duan, & Cadden, 2019). Efficient decision-making constitutes some attributes such as decision-making costs are low (S. Shamim et al., 2019), timely (Ghasemaghaei et al., 2018; S. Shamim et al., 2019), real-time, able to respond quickly to changes (Cao et al., 2015a; Cao, Duan, & Cadden, 2019) and fewer people involved in making decisions (S. Shamim et al., 2019).

5. Research framework and agenda

Scholars argue that business analytics adoption involves technology, people and management factors. Some studies argue that business analytics directly affect firm performance, with different types of performance, such as environmental performance, social performance, economic performance, value creation, customer satisfaction and organisational performance. Other studies argue that the value of business analytics to performance improvement happens by integrating it into the decision-making process. Business analytics leads to a data-driven environment hence improving the decision-making process (Cao et al., 2015b; Ashaari et al., 2020; Ghasemaghaei, 2019; Daradkeh, 2021).

Some scholars argue that decision-making performances, in terms of decision-making quality, effectiveness and efficiency, are the end outcome of business analytics or big data implementation. Hence they put decision-making performance as the dependent variable in their research framework (Wang & Byrd, 2017; Ghasemaghaei et al., 2018; Ghasemaghaei, 2019; S. Shamim et al., 2019; (Saqib Shamim et al., 2020). Some others put performance-related indicators, such as decisions that improve organisational performance and decision that leads to desired outcomes, as the manifest variables of decision-making effectiveness (Wang & Byrd, 2017; S. Shamim et al., 2019; Saqib Shamim et al., 2020). Other scholars put decision-making effectiveness as mediating variable toward performance, such as competitive advantage (Cao, Duan, & El Banna, 2019).

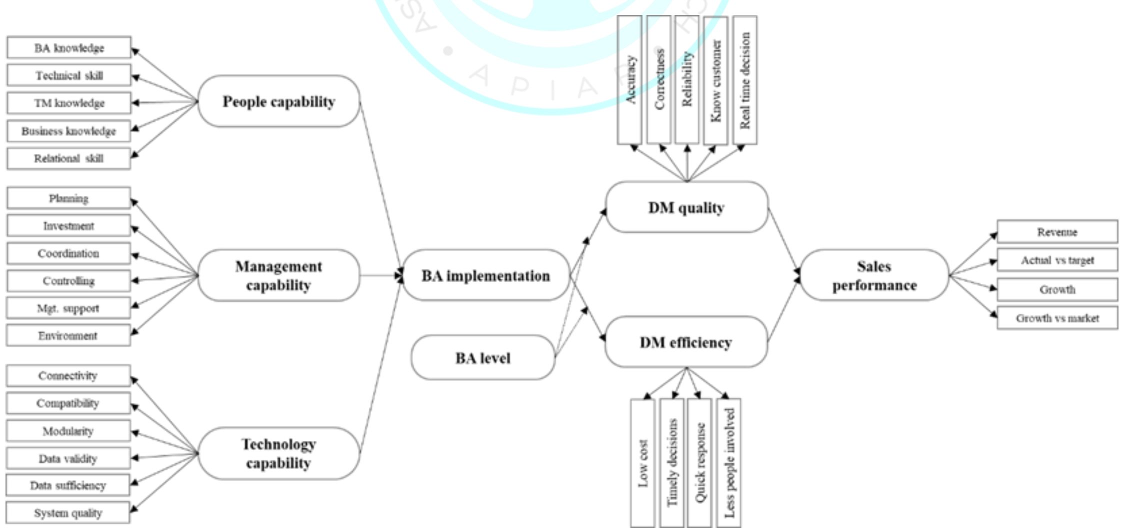

Figure 4. Business analytics framework in the pharmaceutical market

Following Sahay's definition of business analytics as a data-driven decision-making approach (Sahay, 2020), this study argues that business analytics generates insight for decision-making; hence its value is mediated by decision-making quality and efficiency. We propose to combine the two approaches by exploring the technology, people/personnel and management capabilities of business analytics and their integration into the decision-making process. It assumes that business analytics implementation allows companies to generate better decisions or solutions in sales and marketing that eventually will improve sales performance, as shown in figure 4.

6. Conclusion

Pharmaceutical marketing and sales are complex due to the nature of the industry, such as high regulation, no direct engagement with end consumers (patients), complicated disease areas and treatment decisions, marginal benefits with substantial costs, etc. Apart from the complexity, pharmaceutical sales and marketing have been criticised for a long time due to some unethical practices. Heavy reliance on relationship marketing and subjective decision-making are some of the causes of the issue. Hence, a more reliable decision-making process using data or business analytics is necessary.

The pharmaceutical industry is data intensive, especially in the product development stage; however, the marketing and sales operation has not optimally used data to help make better decisions. We conduct a systematic literature review to understand the effective framework of business analytics implementation and its integration into decision-making. Based on the SLR, we identified numerous factors or variables suggested by researchers based on empirical research in other industries. We propose a comprehensive BA framework that combines capability, technology capability, management capability and the mediating role of decision-making to improve sales performance. It is advisable to conduct qualitative exploratory research, such as case studies, to understand the real BA phenomenon in the pharmaceutical market. The case study will reveal BA implementation's motivation, opportunities and challenges and the reason behind them. It will then help to suggest the final BA framework. Further on, a quantitative survey with SEM will help describe the relationship and the magnitude of the relationship between variables.

References

i. Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., Childe, S. J., Fosso Wamba, S., Gunasekaran, A., Dubey, R., Childe, S. J., Wamba, S. F., Gunasekaran, A., Dubey, R., & 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. https://doi.org/10.1016/j.ijpe.2016.08.018

ii. Ashaari, M. A., Amran, A., Ahmad, N. H., Bakri, H., & Nazri, S. (2020). Big Data Analytics Technology Capability and Data-Driven Decision Making in Malaysian Higher Education Institutions: A Conceptual Framework. *IOP Conference Series: Materials Science and Engineering*, *874*(1), 1–7. https://doi.org/10.1088/1757-899X/874/1/012021

iii. Brynjolfsson, E., & McElheran, K. (2016). The rapid adoption of data-driven decision-making. *American Economic Review*, *106*(5), 133–139. https://doi.org/10.1257/aer.p20161016

iv. Cao, G., Duan, Y., & Cadden, T. (2019). The link between information processing capability and competitive advantage mediated through decision-making effectiveness. *International Journal of Information Management*, *44*(July 2018), 121–131. https://doi.org/10.1016/j.ijinfomgt.2018.10.003

v. Cao, G., Duan, Y., & El Banna, A. (2019). A dynamic capability view of marketing analytics: Evidence from UK firms. *Industrial Marketing Management*, *76*(May 2018), 72–83. https://doi.org/10.1016/j.indmarman.2018.08.002

vi. Cao, G., Duan, Y., & Li, G. (2015a). Linking Business Analytics to Decision Making Effectiveness: A Path Model Analysis. *IEEE Transactions on Engineering Management*, *62*(3). https://doi.org/10.1109/TEM.2015.2441875

vii. Cao, G., Duan, Y., & Li, G. (2015b). Linking Business Analytics to Decision Making Effectiveness: A Path Model Analysis. *IEEE TRANSACTIONS ON ENGINEERING MANAGEMENT*, *62*(3), 384–395.

viii. Daradkeh, M. K. (2021). An empirical examination of the relationship between data storytelling competency and business performance: The mediating role of decision-making quality. *Journal of Organizational and End User Computing*, *33*(5), 1–24. https://doi.org/10.4018/JOEUC.20210901.oa3

ix. Frow, P., Payne, A., Wilkinson, I. F., & Young, L. (2011). Customer management and CRM: Addressing the dark side. *Journal of Services Marketing*, *25*(2), 79–89. https://doi.org/10.1108/08876041111119804

x. Ghasemaghaei, M. (2019). Does data analytics use improve firm decision making quality? The role of knowledge sharing and data analytics competency. *Decision Support Systems*, *120*(March), 14–24. https://doi.org/10.1016/j.dss.2019.03.004

xi. Ghasemaghaei, M., Ebrahimi, S., & Hassanein, K. (2018). Data analytics competency for improving firm decision making performance. *Journal of Strategic Information Systems*, *27*(1), 101–113. https://doi.org/10.1016/j.jsis.2017.10.001

xii. Gunasekaran, A., Yusuf, Y. Y., Adeleye, E. O., & Papadopoulos, T. (2018). Agile manufacturing practices: the role of big data and business analytics with multiple case studies. *International Journal of Production Research*, *56*(1–2), 385–397. https://doi.org/10.1080/00207543.2017.1395488

xiii. Handoo, S., Khera, D., Nandi, P., Sahu, S., & Arora, V. (2012). A comprehensive study on regulatory requirements for development and filing of generic drugs globally. *International Journal of Pharmaceutical Investigation*, *2*(3), 99. https://doi.org/10.4103/2230-973x.104392

xiv. Holsapple, C., Lee-Post, A., & Pakath, R. (2014). A unified foundation for business analytics. *Decision Support Systems*, *64*, 130–141. https://doi.org/10.1016/j.dss.2014.05.013

xv. Ji-fan Ren, S., Fosso Wamba, S., Akter, S., Dubey, R., & 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). https://doi.org/10.1080/00207543.2016.1154209

xvi. Lee, D., & Begley, C. E. (2016). Physician report of industry gifts and quality of care. *Health Care Management Review*, *41*(3), 275–283. https://doi.org/10.1097/HMR.0000000000000042

xvii. Lim, W. M., & Rasul, T. (2022). Customer engagement and social media: Revisiting the past to inform the future. Journal of Business Research, 148, 325-342.

xviii. Lim, W. M., Rasul, T., Kumar, S., & Ala, M. (2022). Past, present, and future of customer engagement. Journal of Business Research, 140, 439–458.

xix. Lim, W. M., Kumar, S., Pandey, N., Rasul, T., & Gaur, V. (2023). From direct marketing to interactive marketing: A retrospective review of the Journal of Research in Interactive Marketing. Journal of Research in Interactive Marketing, 17(2), 232-256.

xx. Matikainen, M., Olkkonen, L., Katajavuori, N., Parvinen, P., & Juppo, A. (2017). Physicians' relationship with the pharmaceutical industry and its reflection in introduction of a new drug. *International Journal of Pharmaceutical and Healthcare Marketing*, *11*(3), 309–326. https://doi.org/10.1108/IJPHM-09-2016-0048

xxi. Paich, M., Peck, C., & Valant, J. (2009). PHARMACEUTICAL PRODUCT BRANDING STRATEGIES: Simulating Patient Flow and Portfolio Dynamics. In *Informa Healthcare* (Second Edi). Informa Healthcare.

xxii. Patwardhan, A. R. (2016). Physicians-Pharmaceutical Sales Representatives Interactions and Conflict of Interest: Challenges and Solutions. *Inquiry : A Journal of Medical Care Organization, Provision and Financing*, *53*(December), 1–5. https://doi.org/10.1177/0046958016667597.

xxiii. Rasul, T., Zaman, U., & Hoque, R. (2020a). Examining the pulse of tourism industry in the Asia-Pacific region: A systematic review of social media. Tourism and Hospitality Management, 26(1), 173-193.

xxiv. Rasul, T., Hoque, R., & Arefin, S. (2020b). Social media for web-communities of female entrepreneurs: A PRISMA compliant exploration. International Journal of Web Based Communities, 16(4), 396-409.

xxv. Rasul, T., Lim, W. M., Dowling, M., Kumar, S., & Rather, R. A. (2022). Advertising expenditure and stock performance: A bibliometric analysis. Finance Research Letters, 103283.

xxvi. Ren, S., Zhang, Y., Liu, Y., Sakao, T., Huisingh, D., & Almeida, C. M. V. B. (2019). A comprehensive review of big data analytics throughout product lifecycle to support sustainable smart manufacturing: A framework, challenges and future research directions. *Journal of Cleaner Production*, *210*, 1343–1365. https://doi.org/10.1016/j.jclepro.2018.11.025

xxvii. Saavedra, K., O'Connor, B., & Fugh-Berman, A. (2017). Pharmacist–industry relationships. *International Journal of Pharmacy Practice*, *25*(6), 401–410. https://doi.org/10.1111/ijpp.12333

xxviii. Sah, S., & Fugh-Berman, A. (2013). Physicians under the influence: Social psychology and industry marketing strategies. *Journal of Law, Medicine and Ethics*, *41*(3), 665–672. https://doi.org/10.1111/jlme.12076

xxix. Sahay, A. (2020). Business Analytics A Data-Driven Decision-Making Approach for Business Volume II (Predictive Analytics). In *Business Expert Press* (Volume II). Business Expert Press.

xxx. Sendyona, S., Odeyemi, I., & Maman, K. (2016). Perceptions and factors affecting pharmaceutical market access: results from a literature review and survey of stakeholders in different settings. *Journal of Market Access & Health Policy*, *4*(1), 31660. https://doi.org/10.3402/jmahp.v4.31660

xxxi. Shamim, S., Zeng, J., Shariq, S. M., & Khan, Z. (2019). Role of big data management in enhancing big data decision-making capability and quality among Chinese firms: A dynamic capabilities view. *Information and Management*, *56*(6), 103135. https://doi.org/10.1016/j.im.2018.12.003

xxxii. Shamim, Saqib, Zeng, J., Khan, Z., & Zia, N. U. (2020). Big data analytics capability and decision making performance in emerging market firms: The role of contractual and relational governance mechanisms. *Technological Forecasting and Social Change*, *161*(January), 120315. https://doi.org/10.1016/j.techfore.2020.120315

xxxiii. Torres, R., Sidorova, A., & Jones, M. C. (2018). Enabling firm performance through business intelligence and analytics: A dynamic capabilities perspective. *Information and Management*, *55*(7), 822–839. https://doi.org/10.1016/j.im.2018.03.010

xxxiv. Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review. *British Journal of Management*, *14*, 207–222. https://doi.org/10.1007/978-3-030-92836-0_28

xxxv. Troisi, O., Maione, G., Grimaldi, M., & Loia, F. (2020). Growth hacking: Insights on data-driven decision-making from three firms. *Industrial Marketing Management*, *90*, 538–557. https://doi.org/10.1016/j.indmarman.2019.08.005

xxxvi. Wamba, S. F. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research*, *70*, 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009

xxxvii. Wang, Y., & Byrd, T. A. (2017). Business analytics-enabled decision making effectiveness through knowledge absorptive capacity in health care. *Journal of Knowledge Management*, *21*(3).