Customer Agility and Big Data Analytics In New Product Context

Abstract

New product development is s complicated process in marketing. New product success is an important part of new product development. Firms can use big data analytics to track new product success. Therefore, we develop quantitative research to see how big data analytics can help the firms on the new product success process. Using a survey, we collect data from the industry. The results of our PLS analysis show the effective use of data interpretation tools and effective use of data analysis tools are important factors to share customer agility in new product success. Our research has theoretical contributions and practical implications, which we discuss at the end of the paper.

Keywords:

Customer Agility; Big Data Analytics; New Product Sucess; Survey

1. Introduction

The recent technological advancements are providing new opportunities to businesses. Every organization needs to build its technology intensity to master technology capabilities and implement basic cognition and actions for technological applications. This also means that the level of the technical application of the organization must be based on the tech intensity of trust in technology and partners, which will be the binding force to promote future economic development (Felipe et al., 2020). Data technology will become the technology that defines the future, bringing profound changes to all walks of life.

Nowadays, in an era of the rapid information environment and numerous emerging technologies, it is not surprising that many new products appear in the market, even during the life threats and supply chain crises during COVID-19. Therefore, companies develop new products or improve old products to increase customer loyalty and attract more new customer groups to gain more competitive advantages (Tan & Zhan, 2017). In various new product development cases, the factors that affect the success of new products are classified as product quality, innovation, functionality, brand, and environmental changes (Hajli et al., 2020; Hosseini et al., 2018; Morgan & Liker, 2020). However, in this era, people often reject new products until major technology improvements are available (Heidenreich et al., 2022).

New product development can be classified as a kind of ability. Therefore, understanding customer's desire is an essential element in new product success.

Organizations with this ability can often predict or analyse customer needs and market trends better than other competitors (Awwad & Akroush, 2016). It can adjust correspondingly to changes in environmental factors, thereby enhancing the results and benefits of new product development. The general way to define the ability of a company to succeed in a new product is to compare the sales percentage of a newly listed product based on the sales percentage of the previous year and compare it with the percentage of the total sales of the new year (Dul & Ceylan, 2014). In other words, it is to establish new performance indicators to compare with the old sales performance to know whether the new product development is successful. However, with the accelerating speed of the rise of new technologies, customer needs are constantly changing, resulting in the success of new product development becoming more and more unpredictable. As a result, only innovative products are likely. The rapid changes in the needs of the product lead to a shorter life cycle of the product (Soltani-Fesaghandis & Pooya, 2018). A new product that is successfully sold in the first year is likely to completely lose the market in the next year, causing the company to fail to obtain sufficient profits from the product, only increasing the number of development costs. Based on the business model of traditional companies in the past, although many companies continue to try to develop new products, the failure rate is much higher than the success rate (Bhuiyan, 2011; Cooper, 2019). Therefore, many companies often create new products due to their failure rate. Frustrated in planning, huge investment costs but not enough to make ends meet, leading to difficulties in business operations or even shut down.

Successful firms are using new technologies to improve their ability to analyse and interpret external information can help them analyse market changes, and customer needs more accurately. A business organization with successful product development capabilities does not just have the production capabilities and technologies to develop innovative products. These enterprise organizations often have a strong data processing team and a decision-making team that quickly understands market trends and changes and can analyse and change the situation that may occur after the product is launched in the product development stage. In order to find out the problems, they need to advance and correct the product line process in the research and development process and pre-locate the customer groups in need to achieve the results of Martech's precise marketing. Therefore, the organizational structure and planning of the company are also likely to affect the development of new products (Menguc & Auh, 2010), and companies with a sound organizational structure can do complete planning for product development plans and make more arrangements. Agile teams plan to obtain better product innovation capabilities, reflecting the value of new product development capabilities.

The above-mentioned gap encouraged us to look at the big data analytics elements and their impact on new product success. Previous research on this stream (Hajli et al., 2020) looks at big data analytics with a qualitative lens. However, this research develops a theoretical model (Figure 1.0) with a quantitative approach to understand the role played by the technological intensity of a company's data interpretation and analysis for its organizational agility. Further, understand whether such driven organizational agility can lead to a higher degree of new product success.

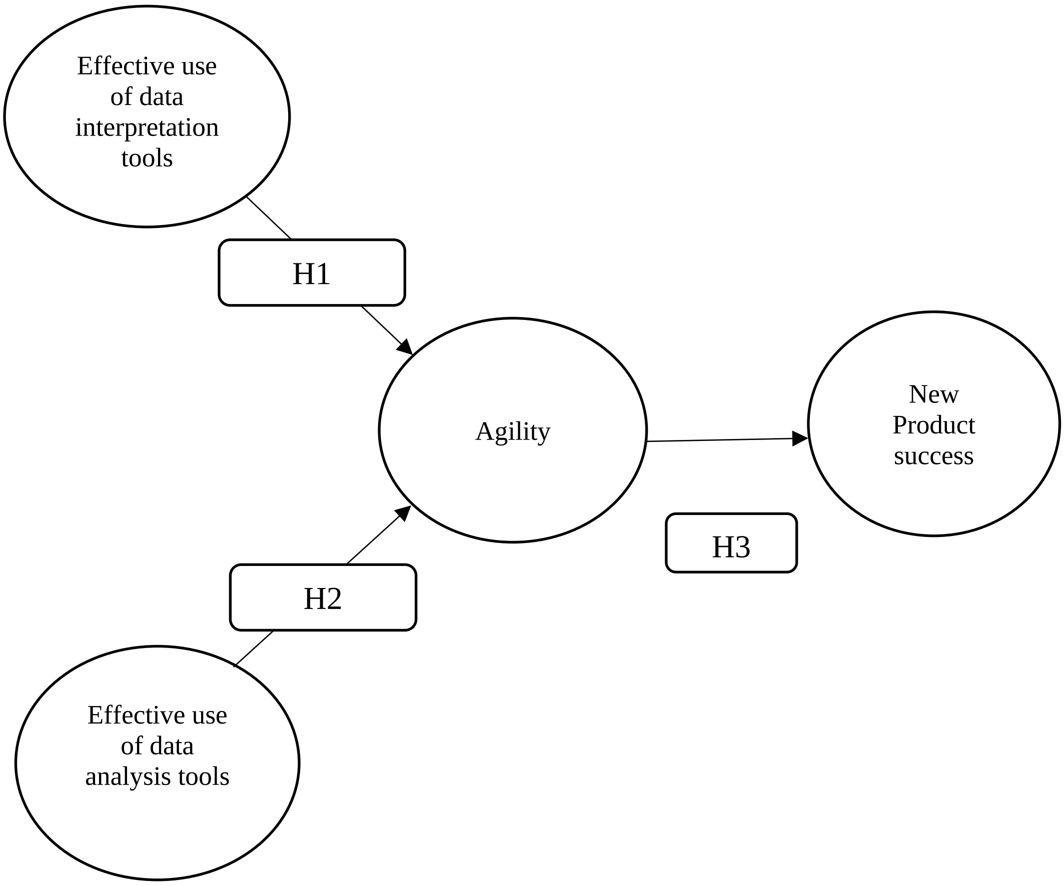

Figure 1.0 The research model

2. Literature review and theoretical foundation

2.1 Technological intensity

The construction of "technological intensity" by enterprises is an important trend of today. Technology intensity pays attention to the adoption of technology and the strengthening of personnel and technology (Abazieva et al., 2016). With the acceleration of new products and the increase in complexity, few manufacturers can entirely rely on their internal R&D resources and experience to construct technical knowledge that quickly responds to market needs to maintain long-term technical advantages (Granstrand et al. In addition to introducing new technologies, the technology intensity of the organization and employees must also be improved. Technology intensity is often used to understand how scientific research has contributed to the increase in industrial productivity and/or income. This intensity is usually measured by the ratio of industry-defined research to its output (Miloud et al., 2012).

When the level of the competitive environment is moderate, the company has fewer competitors and fewer types of competing products. Therefore, the company organization will focus on improving production efficiency and reducing costs in terms of products (Bocken et al., 2016). Nowadays, with the rapid flow of information and the emergence of emerging technologies, the degree of competition in the industry can be said to be a rapid rise in the degree of verticality compared with the past ten years. The influence of the successful development of innovative products on the improvement of corporate organizational competitiveness has led most corporate leaders to increase their efforts to invest more in product innovation. After analysing and evaluating various internal and external uncertain variables by using the product development capabilities and predicting the possible sales success results, the enterprise organization also needs to have the corresponding technical strength to support innovation using emerging technologies product development.

Therefore, the absorption of technical capabilities has become a critical factor that can stabilize the technical strength of the organization. By recruiting talents or acquiring companies and acquiring their technologies, they can obtain this external knowledge or capabilities that are helpful to the organization and operation of the company (Kamal & Flanagan, 2012). Agile organizations have more robust adaptability. While a large amount of external information flows into the organization, these capabilities can be identified and analysed more quickly and efficiently, leaving the most compelling part and integrating and assimilating with the company's operations, production, and management processes (Laviniki et al., 2021). In addition, the most efficient enhancement of the technical intensity of the enterprise organization is also carried out to obtain the maximum level of competition in the industry in the shortest time and provide the most significant guarantee for any possible future product development activities.

2.2 Effective use of data interpretation tools

With the rapid development of information technology, research related to big data technology has become popular. The background of interpretable meaning has expanded, thus making exploration data more diverse and complex. Big data analytics is an emerging approach n business research (Wang & Hajli, 2017). Diversified data integration and interpretation have also become current research trends and challenges. Many studies have also pointed out that effective interpretation of big data will become the most significant trend. Use existing visualization tools and technologies to give meaning to data and maximize the value (Boldosova & Luoto, 2019) to make more efficient decision-making and solve problems. Business strategies and advanced insight advantages often rely on the effective interpretation of the background of these data materials (Münch. 2007). For companies, practising big data interpretation and understanding business, management, and technology-related data will have a strong impact on the company's future operational decisions.

2.3 Effective use of data analysis tools

When performing data understanding, when a data scientist needs to interpret a vast data set, the most difficult challenge is to perform an effective analysis of the data set (Sapountzi & Psannis, 2018). The sources and types of these data are not the same. Some are structured, some are not structured, some data come from many quantified collections, and some are qualitative samples with a small number of samples but extremely diverse content. In the big data environment, related research is constantly exploring how to integrate and visualize more varied data and use this to predict and evaluate the future time axis (Rautenhaus et al., 2017). Companies in the information environment expect to predict and adjust future business decisions through clues learned from the data and collect multiple types of data from various channels. These sources may be market surveys, customer feedback, corporate interviews, etc. Only by integrating, analysing, and visualizing these data can it be reasonably explained and used in the business management of the enterprise. Using those sources of information might also create problem for the companies as the issue of privacy in big data is an important element (Hajli et al,. 2021).

2.4 Agility

Agility originated from software engineering and was initially used in program development to quickly test errors and respond in real time (Lee & Xia, 2010). As various fields began to apply the concept of agile to the company's operating procedures, agile methods began to become more flexible, responding to multiple types of changes at a faster speed and formulating new strategies at any time and were widely used in product development, project management, resource allocation and market forecasting (Ciric et al., 2018; Cooper, 2016). "Manifesto for Agile Software Development", written by several agile software developers in 2001, has become the cornerstone of all agile methods today (Beck et al., 2001). It covers four values, making it applicable to any workflow that requires agile methodologies (Agile, 2001). The four values are: (1) In teamwork, the fixed process of communication between people is more important. (2) It is more critical to develop smooth and usable software than to provide detailed documents. (3) Communication and coordination with customers are more important than fixed contract negotiation. (4) It is more important to respond quickly to changes than follow the plan.

Today’s commonly used agile working methods include Scrum, Agile Modelling, Crystal Clear, etc. These methods have common characteristics such as periodic development time, targeting small projects, and belonging to collocated teams (Hoda et al., 2010). When an enterprise uses these methods, its members will keep in touch with each other and regularly conduct progress checks and tests to solve changing problems and make changes to the work process in response to different situations.

2.5 New Product Success

The success of any new product development is significantly related to the organisation's capabilities. Whether it is acquiring information from the outside or new technologies, many studies on business management and market research have found that companies and organizations actively acquire external information. Whether to obtain market information, emerging technologies, mass consumer habits, and any intelligence of competitors, these companies have achieved a reasonable success rate in the market in the subsequent development of new products (Abid & Gulzar, 2018).

As big data technology becomes more popular and universal, most companies have achieved remarkable results in new product development through more effective data interpretation and data analysis technology. Still, they have also promoted the fierce competition in the industry more quickly. Consumers have become accustomed to the frequency and speed of the launch of new products. They have begun to generate more new demands, which has increased the difficulty of new product development, making it necessary for corporate organizations to collect more information and absorb more new knowledge continuously. Therefore, companies cannot stagnate due to temporary development success and must maintain close contact with customers to understand changes in demand (Baum et al., 2019) to achieve an excellent corporate sustainable operation effect.

3. Hypothesis development

3.1 Effective use of data interpretation tools and agility

In the context of environmental changes that are full of uncertainty due to the availability of information, if the organization follows the past working methods, simply interprets the data and formulates a strategic plan based on the appropriate time, place, conditions, and cost (Swafford et al., 2006), it will be easy for the plan to be interrupted or fail due to changes in the environment, customers and even any possible natural and man-made disasters and other external factors. Therefore, organizations must now have more agile methods for effective interpretation of data in order to respond to any needs that customers may generate or respond immediately (Sjödin et al., 2018). And at the same time, predict any possible risks and formulate emergency response measures when the risks occur to avoid any potential failure or interruption factors. Therefore, we propose research Hypothesis 1 (H1):

H1: The more effective an enterprise uses data interpretation tools, the higher its organizational agility.

3.2 Effective use of data analysis tools and Agility

The development of big data has dramatically increased the value of data analysis. The use of data analysis can help organizations sense changes in the external environment and use this to improve the organization's response speed and operational processes (Ghasemaghaei et al., 2017). With the rapid flow of information and the increasingly fierce competitiveness of enterprises, all enterprises have ushered in an unprecedented era of big data explosion (Chatfield & Reddick, 2018). In order to cope with any changes that may have an impact on the organization, the scope of the original data analysis data collection is also rapidly expanded. Enterprises or organizations that master more agile data analysis technologies will be able to make more distant predictions and prepare in advance for any opportunities, benefits or risks that may arise. At the same time, while improving organizational flexibility, companies can also gain competitiveness that is far ahead of other organizations. Therefore, we propose research Hypothesis 2 (H2):

H2: The more effective an enterprise uses data analysis tools, the higher its organizational agility.

3.3 Agility and New Product Success

The success of new product development is critical to the growth of a company's competitiveness. With the development of new technologies and the acceleration of the flow of information, more complex or more specific customer needs are also continuously increasing (Ogawa & Piller, 2006). If a company can develop new products that meet customer needs and prices under the right time, conditions, and environment, it will gain a huge competitive advantage quickly. As mentioned earlier, according to Hajli et al. (2020), many factors affect the success of new product development, including quality, innovation, functionality, brand, and environmental changes. In this context, whether internal or external environmental changes are the most critical and uncertain factors for the success of new product development. Any changes that may occur may change the organization's original appropriate time, conditions, and customer needs overnight. Traditional development methods and process planning are mainly for planning and control at the initial stage and must ensure the stability of the working environment (Žužek et al., 2021). Organizations need to adopt a more flexible agile new product development model in today's environment. How to make full use of big data analysis technology and effective data interpretation skills with agile organizational execution is an important topic that all enterprises and organizations pay attention to today. Therefore, we propose research Hypothesis 3 (H3):

H3: The higher an enterprise's organizational agility, the higher possibility of its new product success.

4. Research Method

Data

We invited managers from high tech firms. The firms are urban. They produce high tech products. We invited managers by email to participate in our online survey. From 900 emails sent, we have 100 usable responses. Demographic information is available in Table 1.

Table 1: Participant demographics

Demographic	Range	Frequency	Percentage %
Gender	Male	58	58
	Female	42	42
Age	31-40	30	30
	41-50	29	29
	51-60	32	32
	61 or more	9	9
Job Position	Executive	10	10
	Manager	83	83
	Senior Staff	7	7
Firm Size	<200 Employees	10	10
	200-500 Employees	15	15
	500-1000 Employees	25	25
	1000> Employees	50	50
	Total Responses	100	100%

Measurement

The measurement items have been adopted from previous research. Participants have been asked to rate the items by using a 5-point response scale (from 1 = *low* to 5 = *high*). Agility, effective use of data interpretation tools and effective use of data analysis tools have been adopted from Shirazi et al., (Shirazi et al., 2021). New product success has been adopted from Chen et al., (Chen et al., 2005).

4.1 Data Analysis and Results

We use structural equation modelling (SEM) and partial least square (PLS) to analyse our model. We use SmartPLS software version 3 to test the model.

5.1 Measurement Model Analysis

In this section, we report our construct's reliability and validity results. As it is shown on Tabel 2, composite reliability (CR) values range from 0.885 to 0.953. Furthermore, it highlights the cut-off value of .70, ensuring construct reliability in this research. Again, the average variance extracted (AVE) values exceed the suggested standard of 0.50. These results show the required reliability and convergent validity. Finally, Cronbach's Alpha for all constructs is above 0.70.

Table 2: Construct Reliability and Validity

Constructs	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Agility	**0.944**	**0.953**	**0.717**
Effective use of data analysis tools	**0.869**	**0.909**	**0.715**
Effective use of data interpretation tools	**0.841**	**0.894**	**0.738**
New Product success	**0.827**	**0.885**	**0.659**

We also report the Fornell-Larcker Criterion, the square root of AVE for each construct. The value for each construct is higher than the correlation between any pair of distinct constructs.

In addition, non of the correlation coefficients value exceeds 0.70, which confirm discriminant validity for our research (Fornell & Larcker, 1981; Sepasgozar et al., 2019; Urbach & Ahlemann, 2010; Yukl et al., 2008).

Table 3: Fornell-Laker Criterion

Constructs	Agility	Effective use of data analysis tools	Effective use of data interpretation tools	New Product success
Agility	0.847			
Effective use of data analysis tools	0.671	0.846		
Effective use of data interpretation tools	0.323	0.755	0.859	
New Product success	0.592	0.578	0.386	0.812

Note: Bold values indicate the AVE, and values below indicate the square of correlations

The final criterion used for discriminant validity is the report of the cross-loading value across all constructs. As it is shown in Table 3, the factor loadings are higher than all other constructs loading with the circumstance that the threshold value of 0.70 is met (Hair et al., 2006).

Table 3: Cross loading

Constructs	Agility	Effective use of data analysis tools	Effective use of data interpretation tools	New Product success
CA1	0.901	0.648	0.289	0.649
CA2	0.852	0.604	0.293	0.688
CA3	0.91	0.492	0.192	0.541
CA4	0.859	0.55	0.191	0.568
CA5	0.751	0.274	0.065	0.207
CA6	0.754	0.626	0.354	0.211
CA7	0.846	0.671	0.395	0.438
CA8	0.885	0.558	0.34	0.467
EUDAT1	0.736	0.819	0.397	0.488
EUDAT2	0.5	0.882	0.747	0.496
EUDAT3	0.445	0.909	0.836	0.474
EUDAT4	0.478	0.766	0.694	0.482
EUDIT1	0.326	0.729	0.914	0.242
EUDIT2	0.077	0.56	0.773	0.231
EUDIT3	0.296	0.63	0.883	0.48
NPS1	0.666	0.531	0.315	0.92
NPS2	0.381	0.341	0.215	0.825
NPS3	0.399	0.443	0.258	0.777
NPS5	0.382	0.556	0.491	0.712

Structural Model

In the structural model analysis, we start with the model's fit. The results show an adequate structural model fit as SRMR needs to be less than 0.10, and NFI needs to close 1. The results of our PLS analysis are shown in Table 4, and the absolute fit measures are x^2/df = and SRMR= 0.141, which meets the requirements. As such, the results show evidence of a good model fit.

Table 4: Model fit

	Saturated Model	Estimated Model
SRMR	0.141	0.148
d_ULS	3.768	4.166
d_G	4.151	4.168
Chi-Square	1511.276	1517.087
NFI	0.471	0.469

We use PLS to analyse the hypotheses. All three hypotheses are supported. The $\boldsymbol{H_1}$ and $\boldsymbol{H_2}$, and $\boldsymbol{H_3}$ predict the relationships between the variables. The results shown in figure 2 indicate the effective use of data interpretation tools, and the effective use of data analysis tools positively influence agility. In addition, agility positively impacts new product success. The adjusted R-square shows that variations of the effective use of data interpretation tools and the effective use of data analysis tools explain 53% of the variation of agility. Finally, the adjusted R-square shows that variations of agility explain 36% of new product success.

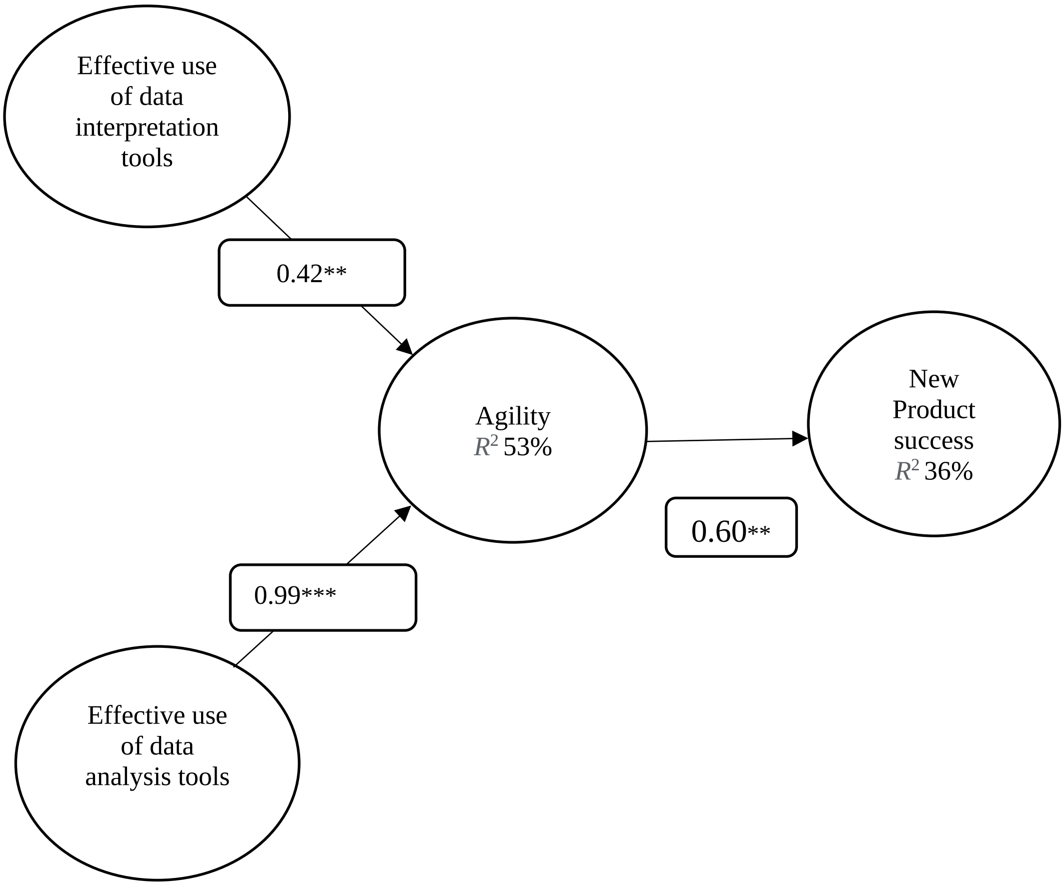

Figure 2.0 Structural Model
Note: **p<0.01; *** p< 0.001

5. Discussion

The results show that the effective use of data interpretation tools and effective analysis tools influence customer agility, leading to new product success. Sales expectations measure new product success, profit expectations, return on investment (ROI) expectations, overall senior management's expectations, and market share expectations which can be enhanced by the effective use of data interpretation tools and effective use of data analysis tools along with customer agility. Firms by effective use of data analysis tools such as identifying essential business insights and trends to improve product development, predicting product patterns in response to customers' needs, analyzing data in near-real or real-time that allows reactions to unexpected market threats and analyzing social media data to understand current trends from a large population can help the business to have a better understanding of the market for new product success. In addition, firms by effectively using data interpretation tools such as providing systemic and comprehensive reporting to help recognize feasible opportunities for product improvement, supporting data visualization that enables users to easily interpret results and providing near-real or real-time reporting for the products can also help the new product success. The results of our analysis show, firms by integrating the effective use of data interpretation tools and effective use of data analysis tools, can develop customer agility In from of customer sensing capability and customer responding capability. The results show with those analytics tools; firms can have a better customer sensing capability by continuously discovering additional needs of our customers of which they are unaware and extrapolating key trends to gain insight into what users in a current market will need in the future. It also helps them continuously anticipate our customers' needs even before they are aware of them and attempt to develop new ways of looking at customers and their needs. This research also confirms the previous findings (Hajli et al., 2020 & Shirazi et al., 2021) that those analytics tools help firms enhance customer responding capability by responding rapidly if something important happens concerning the customers and quickly implementing their planned activities about customers. In addition, it allows them to react promptly to fundamental changes concerning our customers, and when they identify a new customer need, they are quick to respond to it.

6. Theoretical contributions and practical implications

The research has a theoretical contribution to the marking field. We integrate customer agility and big data analytics, including the effective use of data interpretation tools and effective analysis tools to study new product success. The current research confirms the previous findings (Hajli et al., 2020). Our contribution is to duplicate the previous research by Hajli et al. (2020), which looked at big data analytics with a qualitative lens. We use the same theoretical framework to develop a theoretical model (Figure 1.0) using a quantitative method. Our contribution is that we explain the role played by the technological intensity of a company's data interpretation and analysis for its organizational agility. We also highlight driven organizational agility can lead to a higher degree of new product success.

This theoretical development in new product development takes a new direction on this field to have more research on new product success with big data analytics theoretical lense.

The findings also provide practical contributions to the firms. Our research results help companies understand the importance of big data analytics in new product success. Our research highlights the importance of using the effective use of data interpretation tools and effective analysis tools to track customer agility for new product success. As new product success is a complicated process, our research model provides a better solution to address the challenges in this field.

7. Limitations and future research direction

This research has some limitations. First, the dataset needs to be more significant to have more samples. The current research could not attract more participants to the study. This will help the authors to have a better position on the generalisability of the results. Therefore, future research may collect more data from different industries to have a better dataset. The second limitation is the lack of a control variable. Some factors might affect the results, such as the company's size. Therefore, future research needs to collect other dimensions of the companies to consider them as the control variable.

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