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Linking business intelligence with the performance of new service products: Insight from a dynamic capabilities perspective

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A B S T R A C T

There are ongoing predictions that business intelligence (BI) capabilities will lead to the improved performance of new service products (NSPs). However, theoretical and empirical research have yet to explain the nature of this contribution. Based on dynamic capability theory, the current research suggests a model explaining how BI capabilities could impact the performance of NSPs. Specifically, it suggests that BI capabilities could lead to better NSP performance by facilitating proximal conditions of NSP, including customer value anticipation capacity, NSP innovativeness capacity and new product speed to market capacity. The results, based on responses by 583 service firms' marketing and sales directors, indicated that benefits from BI capabilities could be realised indirectly via their intermediate impact on proximal conditions, which in turn influence the outcome of the impact of variables on NSP performance. The contribution of this research is a better theoretical understanding and advanced managerial insight into practices on the use of BI as a tool to enhance NSP performance instead of relying on the prevailing anecdotal evidence.

Introduction

Developing new service products (NSPs) has become a competitive necessity in many service industries worldwide, particularly in the current harsh business environment (Chen et al., 2016). Both rapid technological progress and the globalisation of services put firms under pressure to offer new services aimed at attracting new customers, increasing the loyalty of current customers, creating new opportunities and ultimately enhancing the profitability of the firm (Wirtz et al., 2021). Research indicates that about 25% of revenue comes from launching new services and products (Buffoni et al., 2017); service industries contribute about 61% of the global gross domestic product (Statista, 2020).

Nevertheless, developing NSPs is not an easy task and is associated with a relatively high risk of failure (Buffoni et al., 2017; Wirtz et al., 2021). Many NSPs are intangible, complex and not well defined, making it hard for customers to differentiate between several offerings and recognise what they are receiving for their money (Wirtz et al., 2021). Given these characteristics, researchers and practitioners have made considerable efforts to understand and increase the performance of NSPs. Extensive attention has recently been directed to the implementation of BI, as it unveils new insights and hidden patterns that are useful for the development of NSPs (Božič & Dimovski, 2019; Dubey et al., 2021; Tseng et al., 2022). Furthermore, BI involves a variety of technologies, applications, systems and analytic techniques that are designed to help firms meaningfully analyse various market and business data and information (Božič & Dimovski, 2019; Caseiro & Coelho, 2019; Huang et al., 2022).

Because of BI's computational and analytical capabilities, many technology vendors and scholars have anecdotally claimed that BI has the potential to increase the performance and success of NSPs (Dubey et al., 2021; Tseng et al., 2022), with seemingly limited scientific evidence or insights into how it can do this. Contrary to the optimists' expectations, research has reported that many of the early adopters of BI are struggling to achieve the desired outcomes, and many failures have been reported (Xu et al., 2016). Bannister and Connolly (2020) noted that much of the potential of new technologies has been overrated and that many of the expectations were, in fact, wrong. To offer scientific managerial recommendations on the use of BI, it is imperative to empirically investigate the influence of BI on the performance of NSPs and to identify the theoretical process through which BI produces the desired outcomes. These imperatives are among the subjects of this study.

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While the link between BI and performance of NPS is unclear, perhaps because of the newness of the topic, market research has established that the performance of NSPs is largely enhanced by three distinct yet highly complementary proximal conditions, which we predict are strongly associated with the capabilities of BI. These conditions include customer value anticipation (Flint et al., 2011; Joshi & Sharma, 2004; Zhang et al., 2016), NSP innovativeness (Anning-Dorson et al., 2017; Fang, 2008; Oo et al., 2019) and speed to market (Cheng & Yang, 2019; Fang, 2008; Wu et al., 2020, 2017). First, realising customer value is the basis of marketing, making it possible to design successful services and products that meet customers' values and expectations (Zeithaml et al., 2020).

Nevertheless, customer value is not a stable indicator, as what is valued evolves and changes over time. This suggests that firms should be able to predict what customers will value in order to continually meet their expectations (Flint et al., 2011; Zhang et al., 2018). The process of customer value anticipation is very complete and affected by a wide range of elements, elucidating the trade-off between "give" and "get" elements (Kumar & Reinartz, 2016). Doing this effectively requires sophisticated analytical tools. The data/information integration and analytical capabilities of BI do much to enhance the understanding of the dynamic nature of customer value (Choi et al., 2020; Dubey et al., 2021; Tseng et al., 2022), and thus the customer value anticipation capability.

Second, NSP innovativeness, which reflects the extent to which the NSP is unique and meaningful to customers as compared to competing alternatives, offers the opportunity for greater NSP performance in the market (Fang, 2008). Generally, innovativeness requires a fresh perspective (Caseiro & Coelho, 2019). As they can predict many hidden patterns and trends, BI capabilities could also facilitate developing new logic and innovative insight (Božič & Dimovski, 2019; Cheng et al., 2020; Fink et al., 2017), and overcoming the prevailing knowledge rigidity that inhabits organisational learning.

Third, merely anticipating customer value and developing innovative NSPs may not be sufficient to guarantee NSP performance. Speed to market, which represents the time elapsed between the initial conception of the NSP and its launch in the marketplace, is also required (Fang, 2008) because first movers usually harvest prizes (Varadarajan et al., 2008). Timely and fresh information provided by BI could accelerate decision making during the NSP development process, thus reducing time to market.

As yet, these assertions are merely conjectures about the contribution of BI to NSP performance and have not been formalised in a theoretical model. Grounded on dynamic capabilities theory, the aim of this study is first, to add to the existing knowledge base by developing and empirically examining a nomological network that links BI capabilities, customer value anticipation, NSP innovativeness and the speed to market to NSP performance. Achieving this aim facilitates a better theoretical understanding and advances managerial insight and practice in the use of BI as a tool to enhance NSP performance, instead of relying on the prevailing anecdotal evidence.

Moreover, this research aims to test the proposed model in developing countries' contexts, particularly the Arab context. Recently, BI systems have largely been employed by firms in Arab countries, such as Egypt, Saudi Arabia and Jordan. As yet, limited evidence is available in the current literature about the contribution of BI systems to product and firm performance in Arab countries. While designers and producers of BI systems are from notable leading companies in industrialised countries, BI technology transfer to Arab countries could be problematic because of cultural bias in favour of the designers' and producers' own social and cultural systems (Straub et al., 2001). Developing countries, including Arab countries, could encounter social and cultural obstacles while attempting to transfer BI technology, created abroad, into practice at home. Therefore, offering evidence about the impact of BI systems in the Arab context would offer significant insight into how BI systems would perform in this unique context.

Theory and hypothesis development

Dynamic capability theory (DCT) is a highly nuanced theory used to underpin the role of BI (Mikalef et al., 2018). It is an extension of the resource-based view (RBV) of a firm. While RBV suggests that a firm could attain sustained competitive advantages by utilising its own bundles of resources and capabilities, DCT puts forward several propositions to elucidate how the firm could maintain a competitive advantage in rapidly changing and unpredictable business environments (Gonzalez, 2022; Zheng et al., 2011). However, in a dynamic environment, gaining resources alone is insufficient to maintain a competitive advantage. If a firm wishes to gain a competitive advantage, it must restructure its resources into dynamic capabilities (Teece, 2007).

To face changing and seemingly unpredictable business conditions, DCT suggests that firms should always find ways to look through the fog of uncertainty and gain vision to develop dynamic capabilities (Gonzalez, 2021; Kaur, 2022; Rehman et al., 2021; Teece, 2007). Teece et al. (1997) described dynamic capabilities as the capacity to consistently combine and restructure a firm's resources to acquire a competitive advantage in a dynamic business environment. The existing literature describes dynamic capabilities as a set of identifiable and specific routines that are directed towards independent actions.

A set of routines that constitute the dynamic capability of a firm: acquiring and filtering information from both inside and outside the firm about technology, markets and competition to enable the firm sense this information and work out the implications for managerial action (Teece, 2007). Accordingly, a firm should continuously scan, search and explore its environment to identify and seize opportunities and maintain competitiveness.

In the context of the BI literature, studies have treated BI initiatives as a firm's dynamic capabilities, enabling it to sense and seize opportunities in a dynamic market. BI refers to "*decision support systems that are based on the integration and analysis of organisational data resources to improve business decision making*" (Fink et al., 2017, p. 5). It is often used to describe a variety of data analysis and mining techniques to generate a larger body of knowledge and allow for high-quality decision making (Fink et al., 2017). Furthermore, it is used to monitor and absorb information from a dynamic environment to recognise a potential opportunity while mitigating the risks associated with uncertainty (Tarek et al., 2016).

Fink et al. (2017) defined a BI system as "*technical artefacts that provide consumers with BI capabilities*" (p. 5). Capabilities are recurring sequences of activities in asset utilisation, while assets are described as anything physical or intangible which the firm may use in its process (Thomas et al., 1996). Assets are the basic unit of analysis, and capability is the capacity of a group of assets to work in coordination to achieve a common goal (Grant, 1991). Hence, firm assets are fundamental components of a firm's capabilities, as they reflect integrated and coordinated asset arrangements (Teece et al., 1997). Chen and Lin (2021) explained that BI can transmute data into information that can be used to create a new strategy and operational plans, as well as activities that can increase the quality of strategic analysis, decision making and plan execution.

Regarding DCT, Chen and Lin (2021) argue that BI as a system has internal mechanisms "to sense environmental changes and transform new cognitive knowledge into an appropriate action mode to optimize business process and resource allocation, thus generating a systematic capacity to drive organizational decision making and enhance operating efficiency and effectiveness". As organisational dynamic capabilities, BI systems should comprise repeatable patterns of actions in performing a firm's activities (Cheng et al., 2020; Fink et al., 2017).

Three types of BI capabilities are distinguished: strategic capabilities, operational capabilities and data integration capabilities. Strategic BI capabilities entail the use of BI systems to support strategic organisational activities, including identification of opportunities, threats, assessment of risk and trends in the business environment, providing critical insights in developing new corporate strategies. On the other hand, operational BI capabilities involve the use of BI systems to support operational organisational activities, such as using many forms of data analysis within operational activities, sharing information across business units and modelling and optimising service and production processes (Fink et al., 2017). Finally, data integration capabilities involve the integration of observable data from various sources to produce descriptive information about who, what, when and how much the unified dataset influences (Cheng et al., 2020; Ferraris et al., 2019; Fosso Wamba et al., 2015).

Due to its computational and analytical capabilities, extensive attention has recently been directed to the implementation of BI to increase the performance and success of NSP (Choi et al., 2020). Most of the evidence for the impact of BI on NSP performance and success is anecdotal, with little empirical research (Choi et al., 2020). While empirical research finds a significant relationship between BI capabilities and firm performance in general (Caseiro & Coelho, 2019; Chen & Lin, 2021; Huang et al., 2022), the link between them is unclear in the literature, and the underlining processes explaining such a link are virtually absent.

Based on DCT, this study suggests a model explaining how BI capabilities could impact NSP performance through the proximal conditions of NSP. Marketing research has established that the performance of NSP is largely influenced by three distinct yet highly complementary proximal conditions, which we predict are strongly associated with BI capabilities. These conditions are customer value anticipation (Flint et al., 2011; Zhang et al., 2016); NSP innovativeness (Anning-Dorson et al., 2017; Fang, 2008; Oo et al., 2019); and speed to market (Cheng & Yang, 2019; Fang, 2008; Wu et al., 2020, 2017). Fig. 1 depicts the suggested associations. The following sections explain the associations between these conditions and BI capabilities.

BI and customer value anticipation

Customer value anticipation capacity denotes a firm's capacity to predict what specific consumers would value, such as their product and service offerings, as well as the advantages they provide, given the monetary and non-monetary sacrifices required to attain those benefits (Flint et al., 2011); in other words, the firm's capacity to perceive, foresee and predict what individual consumers would value from its products. The most difficult part of developing a successful NSP is designing a service that fits customers' values (Wirtz et al., 2021), as what customers value evolves and changes over time. This suggests that firms should be able to anticipate what customers will value to continually meet their expectations from NSPs. Knowing what consumers will value gives firms enough time to plan a response and to be ready when changes occur (Haryanto et al., 2018; Zhang et al., 2016).

As a process, customer value anticipation is dynamic and in constant flux, necessitating firms' predictive capacities. BI capabilities, that is, strategic, operational and data integration capabilities, help firms predict customer value by providing easy interactive access to a variety of data; employing many algorithms to identify, classify and predict customers' needs; and conducting a wide variety of analyses that provide new insights into what customers really need and value (Chen & Lin, 2021; Dubey et al., 2021). For instance, firms may utilise predictive analytics to accurately anticipate their consumers' demands, sometimes even before they make a decision. Predictive analytics can anticipate any alterations in customer attitudes early on (Choi et al., 2020; Dubey et al., 2021; IBM, 2020). Furthermore, predictive capabilities enable businesses to be proactive, allowing them to modify communications in advance and effectively serve consumers.

In addition, collecting and analysing significant amounts of timely feedback and opinions from a variety of customers can result in social and business insights that are crucial for realising customer value (Chen & Lin, 2021; Cheng et al., 2020), thus contributing to developing more successful new services. For example, using web analytic systems to analyse consumer web browsing data logs to track a user's online activity and reveal his/her browsing history, such as purchase behaviours. BI technologies enable firms to obtain insight into new

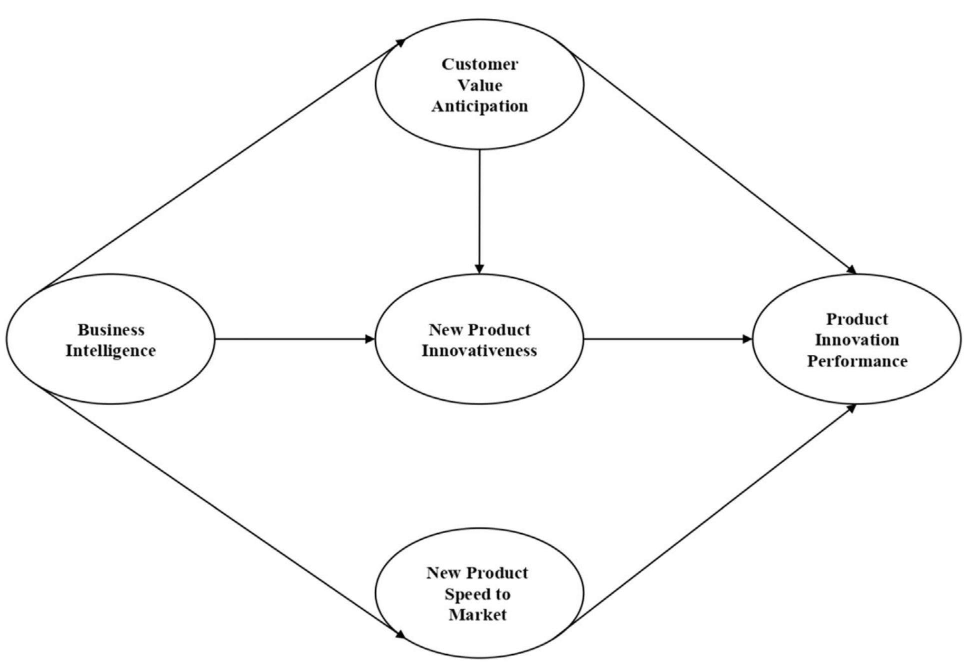

Fig. 1. Conceptual model and hypotheses.

markets, analyse the demand and acceptability of goods and services for various market groups and measure the effect of marketing activities (Cheng et al., 2021; IBM, 2020). Data gathered from various channels and platforms will aid in predicting customer value. Thus, the following relationship is hypothesised:

H1: BI capabilities are positively related to firms' customer value anticipation capacity.

BI and new product innovativeness

New product innovativeness is a major driver of market success, referring to the degree of novelty and creativity of a new product (Eiteneyer et al., 2019). Management may govern innovation by participating in experimental and innovative approaches that lead to new products, services or technological procedures. Consumer (market) demand, rivals' actions or government regulations are factors that influence and even drive a firm's involvement in its creative activities (Prajogo, 2016).

However, creating innovative products requires that information acquired through new product development arouse insightful and novel ideas that cause employees to identify potential new markets or understand current markets from a fresh perspective (Brockman & Morgan, 2003). Because BI capabilities can predict many hidden patterns and trends, they could also facilitate the development of new logic and innovative insight (Božič & Dimovski, 2019; Cheng et al., 2020; Fink et al., 2017), and overcome the prevailing knowledge rigidity that inhabits organisational learning. Extant literature corroborates the link between BI and innovativeness (Caseiro & Coelho, 2019; Tunc-Abubakar et al., 2022), as BI capabilities contribute towards organisational learning (Arefin et al., 2020). Furthermore, the relationship between innovation and organisational learning (Calantone et al., 2002) and past knowledge is important, since it may help in understanding new technologies and market situations, as well as the inception of new ideas and products.

Firms with greater innovation ability can react to environmental challenges quicker and more effectively than non-innovative firms (Cepeda-Carrion et al., 2012). A firm's capacity to convert and use information may influence its degree of innovation, such as creative problem-solving techniques and new products/services offerings, to respond quickly to market demand (Wang & Wang, 2012). Because BI is focused on the utilisation of data to make better choices, this may affect a firm's innovative pursuits. Better information does not automatically lead to improved firm performance and efficiency; what matters is what businesses do with it (Lukman et al., 2011). We hypothesise that obtaining knowledge and making better use of it can have a favourable impact on the innovativeness component. Thus, we propose the following hypothesis:

H2: BI capabilities are positively related to new product innovativeness.

BI and speed to market

Speed to market is defined as "the rate at which activities occur between the conception of an idea and the realisation of a product" (Menon et al., 2002). The term specifically relates to how rapidly an idea moves from conception to market launch (Acharya et al., 2020). Furthermore, speed to market is a critical factor for product innovation performance (Wang et al., 2011). From developing prototypes to deciding on a final design, product development is a time-consuming and difficult process.

In time-based competition, the speed of new product development presents an advantage (Wu et al., 2017). Developing the capability to rapidly develop and introduce new products is a challenging task (Ferreras-Méndez et al., 2022), requiring a special capability to be done effectively. Recently, many firms have begun to utilise BI systems to improve decision-making processes, enabling them to gain a competitive advantage (Park, 2021).

In unpredictable conditions, speed to market is dependent on the most recent market intelligence, requiring firms to react swiftly to changing market needs and demands (Atuahene-Gima & Li, 2017). The strategic capabilities component of BI helps in identifying patterns, opportunities and risks in the business environment, while the operational capabilities component helps in sharing information across business units; the data integration capabilities component helps in gathering descriptive information (Fink et al., 2017). Together, these three components help firms achieve agility and speed to market (Ashrafi et al., 2019). Timely and fresh information provided by BI could also facilitate the speed of decision making during NSP development, and consequently, the speed to market. Thus, the following hypothesis is proposed:

H3: BI capabilities enhance the speedy entry of NSPs into the market.

Customer value anticipation and new product innovativeness

The capacity to anticipate customer needs and values is the key to developing innovative products. From the standpoint of the firm, the new product development process involves the identification, development and introduction of innovative products (Yadav et al., 2007). The term "*identification*" relates to the process of finding new technologies and recognising consumer value. Learning about customer preferences is beneficial, especially at this stage of the new product development phase. Based on this process, customer value anticipation capacity enables the firm to identify customer needs and create new information, which are necessary components for designing innovative products. This capacity seeks to forgo and continuously develop the total present value being produced and moves the status from asking, "What can we do for you today?" to "What should we be doing to prepare for my interactions with you tomorrow?" (Flint et al., 2011; Zhang et al., 2016). In other words, customer value anticipation capacity empowers firms with "need and value knowledge" that enable them to design innovative products to satisfy customers' needs and value. Furthermore, from the consumer's perspective, the better the capability of the firm to anticipate customer needs, the higher the perception of new product innovativeness (Chuah et al., 2018). Thus, the following hypothesis is postulated:

H4: Customer value anticipation capacity is positively related to new product innovation.

Customer value anticipation and product innovation performance

Product innovation performance is the extent to which the resultant new product satisfies the firm's financial and market objectives (Hsiao & Hsu, 2018). The financial objectives include profitability, sales volume and revenue targets for newly launched services and goods (Atuahene-Gima et al., 2005). Product innovation performance is a key measure of return on investment from new products and services. The creation of customer knowledge, that is, gaining insight about the customers' liking and preferences, and value acquisition has been highlighted as a critical pre-condition for new product success (Cooper & Kleinschmidt, 2016). A major cause of new product failure is that the items fail to adequately meet client needs and expectations. The accuracy of consumer preference knowledge may be compromised for two reasons: (a) the information has not been thoroughly checked and (b) customer preferences have not been expected (Joshi & Sharma, 2018). Anticipation of customer value is a business strategy that requires firms to predict the changing needs and wants of their customers. This strategy empowers firms to pay more consideration to what they can do to recognise these changing needs and wants in their new products (Yang & Zhang, 2018). Realising customer values is the basis of marketing, making it possible to design successful services and products that meet customers' values and expectations (Zeithaml et al., 2020). Business strategies that are leaned towards reflecting customers' values and needs are more able to develop high-quality products appreciated by consumers. Accordingly, the following hypothesis is proposed:

H5: Customer value anticipation capacity is positively related to product innovation performance.

New product innovativeness and product innovation performance

Innovativeness makes it easier to pursue new possibilities by introducing new goods and services to the market. If these initiatives succeed, they will influence and improve product performance (Su et al., 2015). More inventive firms will be better at responding to customers' requirements, and developing new skill sets will enable them to improve their performance or profitability. We should expect a relationship between these constructs, since research has steadily given greater attention to the impact of different characteristics of innovation on business performance (Wang & Wang, 2012). The swiftness of obtaining fresh information relating to the innovative product/services development project lowers the time and money spent on research, resulting in improved new product performance. Thus, the following hypothesis is proposed:

H6: New product innovativeness is positively related to product innovation performance.

Speed to market and product innovation performance

Competitive performance is triggered by adapting to changing environments by launching new products more quickly (Teece, 2007). Firms that succeed in achieving radical breakthroughs may gain a competitive advantage (McDermott & O'Connor, 2002). Bringing products to market early enables the use of state-of-the-art components available from technology suppliers, resulting in the most up-to-date products/services, which are hence regarded to be of better quality (Kessler & Bierly, 2002).

Moreover, a reduced development cycle enables more current customer input to be taken into account, allowing for higher customer response and improving consumer perceptions of quality (Brucks et al., 2000). As a result, firms with fast new product development cycles are perceived as more likely to deliver high-quality goods. Additionally, innovative products and services introduced within a short time frame attract huge market demand (Gao et al., 2021). Allowing too much leeway in a development timeline, conversely, might lead to a loss of concentration and discipline in the development process, resulting in inferior-quality output. Delivering high-quality products will lead to higher performance. Thus, we propose the following hypothesis:

H7: Speed to market is positively related to innovative product performance.

Mediating effects

As described earlier, BI capabilities could contribute to the proximal conditions for a successful NSP. The benefits from BI capabilities could be realised indirectly via their intermediate impacts on proximal conditions (customer value anticipation, innovativeness of NSP and new product-to-market speed), which in turn influence the outcome of the impact of variables on NSP performance. Accordingly, proximal conditions could mediate the positive impact of BI capabilities on NSP performance. Therefore, we postulate the following:

H8a: The association between BI capabilities and new product innovation performance is mediated by customer value anticipation capacity.

H8b: The association between BI capabilities and new product innovation performance is mediated by new product innovativeness.

H8c: The association between BI capabilities and new product innovation performance is mediated by new product speed to market.

Methods

Procedures

We designed a structured quantitative survey to gather field data from the marketing and sales directors of leading Egyptian service firms. Because of the COVID-19 outbreak-related restrictions imposed in Egypt, we used Google Forms platform for this purpose. We translated this survey from an English text into Arabic to fit the Egyptian dialect. The pre-testing process of empirical research, as recommended by Olson (2010), requires, at the least, six experts, to assess the consistency of content in the self-administrated survey to detect heterogeneity issues. Therefore, we contacted eight experts (three professors in public management, two associate professors in business administration, two lecturers in service marketing and one deputy director in the marketing department of one of the targeted firms) to review the questionnaire and check the validity of its content.

After a week of communication, five experts confirmed that the Arabic text matched the English text, while the other three suggested minor changes in the interpretation relating to the description of the purpose of each construct. As a result, six days before the actual data collection, a pre-test was conducted on 65 marketing directors from leading Egyptian service firms to define ambiguous eligibility criteria and reduce measurement errors. Of those, 43 responded that the items were easy to understand and were not mysterious. Based on these positive hints, we have moved to the data collection process and the identification of the sampling technique.

Data collection and sampling

A non-probability convenience sampling technique was applied in this study to gather the main data from leading Egyptian service firms (i.e., banks, hospitals, hotels, travel agencies and shipping firms). Participants were chosen using this technique because it is affordable and simple compared to other sampling techniques (Taherdoost, 2018). We chose these firms because they applied micromanagement skill development programmes and strategies. We targeted the marketing and sales directors of these firms for their intimate knowledge of incremental and radical marketing innovations.

Because of our limited knowledge of these directors, we contacted close friends and PhD/MSc students working within these firms to convince their directors to participate voluntarily in our survey. After some communication, these people introduced us to chat groups relating to these directors on LinkedIn, WhatsApp and Telegram. Hence, we informed them that we would provide them with a summary of our findings to improve their long-term marketing operations and sales promotions. Between March and April 2021, we distributed 800 online surveys and received 647 responses, with a response rate estimated at 80.88%, as follows: 98, 177, 152, 96, 65 and 59 from marketing directors of leading firms in banks, hotels, hospitals, travel, insurance and shipping, respectively.

We used a time-lapped approach to control common method bias issues based on a two-wave data collection method. In wave 1, from 7 to 19 March 2021, respondents were asked to provide their views on the extent to which their firms adopted BI and anticipated target customer value to their firms as. In Wave 2, from 23 March−14 April 2021, respondents were asked to provide the degree of development speed of a new product/service, the level of its innovativeness, and the degree to which they were achieved.

Using SPSS v. 26 software, a graphical assessment of the dataset was performed to find outliers using box plots. Consequently, 64 cases were omitted as outliers and the final sample size was 583 valid cases. Krejcie and Morgan (1970) proposed that 384 cases were an adequate sample size for populations of less than a million. Furthermore, the Cohen (1992) rule-of-thumb, which stipulates that a sample size of 583 significantly exceeds the minimum for 80% statistical power at a 5% level of significance, was employed in evaluating the appropriateness of the sample size. Accordingly, this sample size was considered suitable for conducting further statistical techniques. Table 1 presents the respondents' profiles.

Measures

The intended survey in this study consisted of 37 items. We measured BI as a 12-item first-order construct, consisting of three pillars: data integration capability, operational BI capabilities and strategic BI capabilities. Three items developed by Cheng et al. (2020) were used to assess data integration capability. Fink et al. (2017) five and four items were used to assess operational and strategic BI capabilities, respectively. Respondents indicated the degree to which they perceived their firms' BI adoption.

We measured customer value anticipation using a nine-item scale modified from Flint et al. (2011). Respondents indicated the degree to which they anticipated the targeted customers' values of their firms. We also measured new product performance using a five-item scale derived from De Luca and Atuahene-Gima (2007). Respondents indicated the degree of product/service development their firms had achieved. All response options for these constructs were based on a seven-point Likert scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*).

We assessed new product innovativeness using a six-item scale derived from Fang (2008). Respondents rated the extent to which the new component was very ordinary/not creative/uninteresting or very novel/creative/interesting. Finally, we measured new product speed to market with five items adapted from Fang (2008). Respondents rated the extent to which the development speed of the new component was far behind their time goals/slower than the industry norm or far ahead of their time goals/faster than the industry norm. The response options for these two constructs were measured on seven-point differential scales: 1 (*very ordinary/not capable*) to 7 (*very novel/capable*) and 1 (*slower than our typical product/far behind our time goals*) to 7 (*faster than our typical product/far ahead of our time goals*), respectively.

Table 1
Respondents' profiles.

Aspects	*N*	%
Gender		
Male	521	89.4
Female	62	10.6
Marital status		
Single	179	30.7
Married	404	69.3
Age		
< 30 years	89	15.3
30 to < 40 years	28	4.8
40 to < 50 years	414	71.0
≥ 50 years	52	8.9
High educational level		
MSc/PhD.	40	6.9
Diploma	80	13.7
Bachelor	276	47.3
High school	184	31.6
Preparatory school	3	.5
Professional experience		
< 4 years	162	27.8
4 to < 7 years	214	36.7
7 to < 10 years	142	24.4
≥ 10 years	65	11.1
Firm type		
Bank	82	14.1
Hotel	166	28.5
Hospital	140	24.0
Travel agency	90	15.4
Insurance firm	53	9.1
Shipping firm	52	8.9

Common method variance

Given that we adopted a co-measurement approach on all intended scales adapted from a single data source, the responses showed little systematic variation (Fuller et al., 2016). Therefore, we took several steps to assess the common method variance (CMV). Procedurally, construct items were placed randomly to prevent respondents from predicting a cause−effect relationship. The ambiguity of language noted by the academic experts was resolved. The respondents were informed that their information would remain anonymous for publishing online (Podsakoff et al., 2012). For statistical procedures, we followed Kock's (2015) criterion: if the values of the variance inflation factor (VIF) are less than 3.3, there are no multicollinearity issues. Our VIF values ranged from 1.82 to 2.75, which was below the 3.3 threshold. Accordingly, both procedural and statistical remedies indicated that CMV was not a major threat to relationships in the measurement model.

Analyses and results

We adopted partial least square structural equation modelling (PLS-SEM) to analyse the collected data. Because the intended theory is less developed, PLS-SEM was deemed an appropriate analytical technique for this study (Hair et al., 2019). Those authors affirmed the use of PLS-SEM in co-variance-based structural equation modelling in nascent empirical research focused on the theory's exploration. Our current model is relatively complex, as it contains five constructs and several control variables. Because of the prescribed justifications, we assessed the psychometric properties of all reflective constructs using SmartPLS3.0 (Ringle et al., 2015) for the following purposes: a) examination of the proposed conceptual framework; b) estimation of both the measurement and structural models; and c) evaluation of the overall model.

Assessing the measurement model

We examined the item loadings to assess item reliability and to verify abnormalities on all construct scales (Hair et al., 2019). Item loadings ranged from 0.72 to 0.88 (see Table 2), exceeding the recommended threshold of 0.70 and thus presenting strong support for item reliability (Sarstedt et al., 2019). Next, we verified the values for composite reliability (CR) and Cronbach's alpha (α) to examine the internal consistency of the construct reliability. The values of CR and α ranged from 0.91 to 0.93 and from 0.85 to 0.91, respectively (see Table 2). As recommended by Hair et al. (2019), the construct

Table 2
Overview of items and constructs.

Construct	IL	M	SD	CR	α	AVE
Data integration capability		4.91	1.24	0.91	0.85	0.76
Integ_1	0.88					
Integ_2	0.88					
Integ_3	0.86					
Operational BI capabilities		5.12	1.21	0.92	0.90	0.71
Operat_1	0.84					
Operat_2	0.84					
Operat_3	0.84					
Operat_4	0.86					
Operat_5	0.83					
Strategic BI capabilities		4.98	1.21	0.92	0.89	0.75
Strateg_1	0.86					
Strateg_2	0.88					
Strateg_3	0.87					
Strateg_4	0.85					
Customer value anticipation		5.23	1.03	0.92	0.91	0.57
CVA_1	0.77					
CVA_2	0.75					
CVA_3	0.77					
CVA_4	0.72					
CVA_5	0.72					
CVA_6	0.78					
CVA_7	0.76					
CVA_8	0.78					
CVA_9	0.73					
New product innovativeness		5.28	1.12	0.93	0.90	0.68
NPI_1	0.84					
NPI_2	0.82					
NPI_3	0.83					
NPI_4	0.86					
NPI_5	0.79					
NPI_6	0.79					
New product speed to market		5.08	1.08	0.91	0.88	0.68
NPSM_1	0.79					
NPSM_2	0.82					
NPSM_3	0.83					
NPSM_4	0.86					
NPSM_5	0.80					
Product innovation performance		5.10	1.29	0.93	0.91	0.73
PIP_1	0.87					
PIP_2	0.84					
PIP_3	0.86					
PIP_4	0.86					
PIP_5	0.85					

reliability of all values should exceed the 0.70 threshold, which is the case for our constructs.

To assess the convergent validity criterion, we checked the average variance extracted (AVE) of all construct scales (Fornell & Larcker, 1981). These values ranged from 0.57 to 0.76 (see Table 2), exceeding the minimum 0.50 threshold (Hair et al., 2019). Thus, each construct could explain more than 50% of its items, indicating that all constructs had sufficient convergent validity.

To verify the discriminant validity, we used the Fornell−Larcker criterion to assess the items' cross-loadings with outer loadings and the square root of the AVE for each construct, along with the heterotrait-monotrait (HTMT) ratio of all construct correlations (Henseler et al., 2015). First, the findings showed that all items' cross-loadings did not exceed their outer loadings. Second, as shown in Table 3(i), the square root of all AVE ratios for each construct is reported on the diagonal in bold. This indicates that the constructs' shared variances are greater than other constructs' variances (Fornell & Larcker, 1981). Third, the HTMT ratio of average correlations of items across constructs ranging from 0.50 to 0.83 is shown in Table 3(ii). As recommended by Henseler et al. (2015), none of the HTMT ratios in our study exceeded the 0.90 maximum cut-off. This means that all constructs are empirically distinguished from each other, so this model has good discriminant validity.

Assessing the structural model

Using a psychometrically acceptable measurement model, we selected 5000 bootstrapping re-samples in SmartPLS3.0 for two main reasons: first, for testing the proposed hypothesis, and second, for estimating the significance of the standardised path coefficients. We employed complete bootstrapping to test the relevance of the path coefficients, as recommended by Hair et al., Hopkins and Kuppelwieser (2014), since no assumptions related to data distribution were acceptable in PLS-SEM. However, we measured BI using a second-order scale: data integration capability (Cheng et al., 2020), operational BI capabilities and strategic BI capabilities (Fink et al., 2017). Table 4 presents the results of testing the hypotheses.

We concluded that BI is significantly and positively related to CVA (β = 0.59; t = 17.00; $p < 0.001$), new product innovativeness (NPI) (β = 0.60; t = 15.20; $p < 0.001$) and new product speed to market (NPSM) (β = 0.60; t = 16.21; $p < 0.001$), supporting H1, H2 and H3, respectively. Similarly, CVA has a positive and significant relationship with NPI (β = 0.52; t = 11.64; $p < 0.001$), supporting H4. CVA (β = 0.49; t = 13.03; $p < 0.001$), NPI (β = 0.50; t = 12.88; $p < 0.001$) and NPSM (β = 0.15; t = 4.10; $p < 0.001$) have a positive and significant effect on product information performance (PIP). Hence, these findings support H5, H6 and H7.

Table 3
Discriminant validity.

	(i) Correlation matrix Constructs	1.	2.	3.	4.	5.	6.	7.
1.	Customer value anticipation	**0.754**						
2.	Data integration capability	0.541	**0.873**					
3.	New product innovativeness	0.691	0.569	**0.822**				
4.	New product speed to market	0.634	0.506	0.593	**0.822**			
5.	Operational BI capabilities	0.471	0.623	0.464	0.506	**0.843**		
6.	Product innovation performance	0.673	0.573	0.749	0.594	0.449	**0.856**	
7.	Strategic BI capabilities	0.490	0.563	0.469	0.527	0.590	0.480	**0.863**
(ii) Heterotrait-Monotrait ratio (HTMT)								
1.	Customer value anticipation							
2.	Data integration capability	0.62						
3.	New product innovativeness	0.76	0.65					
4.	New product speed to market	0.71	0.58	0.66				
5.	Operational BI capabilities	0.52	0.72	0.52	0.57			
6.	Product innovation performance	0.74	0.65	0.83	0.66	0.50		
7.	Strategic BI capabilities	0.55	0.65	0.52	0.60	0.66	0.54	

Table 4
Results of hypothesis testing.

No.	Path	β	*t*-values	*p*-values	f^2	Support
Direct effects						
H_1	Business intelligence → customer value anticipation	0.59	17.00	0.000	0.54	✔
H_2	Business intelligence → new product innovativeness	0.60	15.20	0.000	0.11	✔
H_3	Business intelligence → new product speed to market	0.60	16.21	0.000	0.57	✔
H_4	Customer value anticipation → new product innovativeness	0.52	11.64	0.000	0.37	✔
H_5	Customer value anticipation → product innovation performance	0.49	13.03	0.000	0.06	✔
H_6	New product innovativeness → product innovation performance	0.50	12.88	0.000	0.32	✔
H_7	New product speed to market → product innovation performance	0.15	4.10	0.000	0.03	✔
Mediated effects						
$H_{8(a)}$	Business intelligence → customer value anticipation → product innovation performance	0.23 [LB = 0.090, UB = 0.196]	5.36	0.000		✔
$H_{8(b)}$	Business intelligence → new product innovativeness → product innovation performance	0.50 [LB = 0.096, UB = 0.199]	5.46	0.000		✔
$H_{8(c)}$	Business intelligence → new product speed to market → product innovation performance	0.15 [LB = 0.046, UB = 0.137]	3.85	0.000		✔
Model fit						
	R^2/Q^2 for customer value anticipation	0.35/0.57				
	R^2/Q^2 for new product innovativeness	0.53/0.35				
	R^2/Q^2 for new product speed to market	0.36/0.24				
	R^2/Q^2 for product innovation performance	0.62/0.45				

Note: LB = lower bound; UB = upper bound.

Mediation testing: post-hoc analysis

To determine the predictive significance of the indirect effects, we used a complete bootstrapping approach and confidence intervals. As recommended by Preacher and Hayes (2008), mediation is achieved when there are no zero confidence intervals and when there is a significant and indirect effect between the predictor and criterion variables. We included the path coefficients of the indirect effects of BI as a predictor variable on PIP as a criterion variable through the mediation of CVA, NPI and NPSM. The findings reported in Table 4 show that BI has a significant indirect effect on PIP through CVA (β = 0.23; p < 0.001, CI = [0.090, 0.196]), through NPI (β = 0.50; p < 0.001, CI = [0.096, 0.199]) and through NPSM (β = 0.15; p < 0.001, CI = [0.046, 0.137]). This indicates that there are partial meditations of CVA, NPI and NPSM in the BI–PIP relationship, supporting H8(a), H8(b) and H8(c). Fig. 2 presents the results of the path coefficients between the putative relationships.

Finally, we extracted the values of R^2, f^2 and Q^2 to evaluate the overall model (see Table 4 and Fig. 2). First, we adopted R^2 values to illustrate the extent to which the model explains variance (Chin, 1998): the model can explain 35%, 53%, 36% and 62% of the variance in CVA, NPI, NPSM and PIP, respectively. Second, the effect sizes (f^2) in the model ranged from weak to strong (0.033 to 0.572), as recommended by Cohen (1988); these values were considered satisfactory and statistically acceptable. Third, we estimated the predictive significance of the endogenous constructs according to Geisser's (1974) and Stone's (1974) criteria. Thus, our structural model showed this predictive significance, as all Q^2 values were greater than zero and close to one.

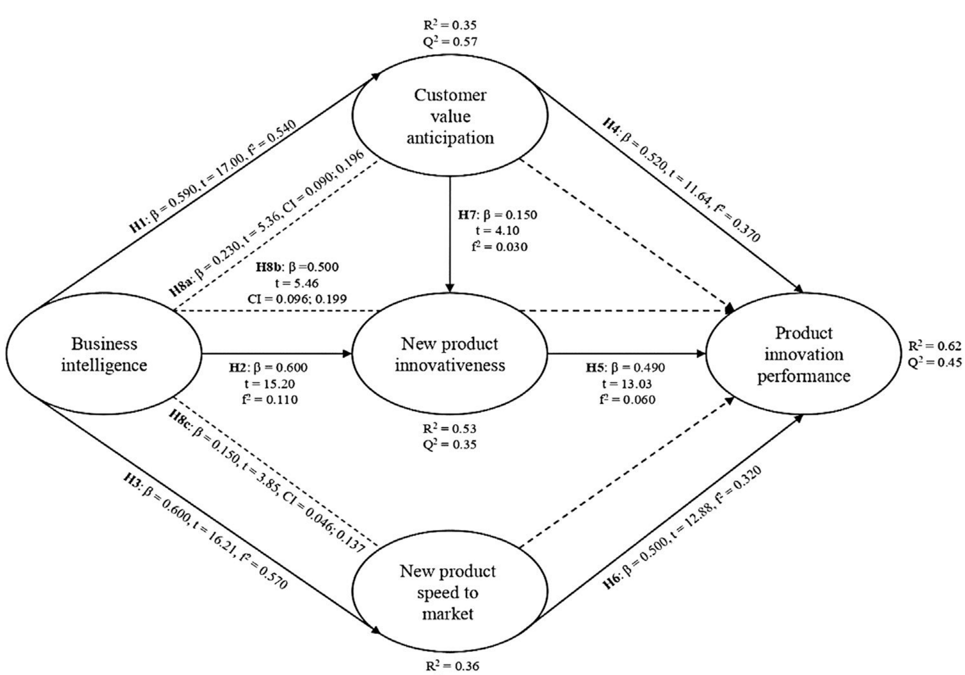

Fig. 2. Results of path coefficients.

Discussion

The objective of the present study was to develop and empirically examine a model describing the processes through which BI capabilities enhance NSP performance. The suggested model considered three important mechanisms, including customer value anticipation, NSP innovativeness and speed to market, which describe the association between BI capabilities and the performance of NSP.

First, our results indicate that BI capabilities are associated with a greater ability to understand and anticipate what customers will value in the future (customer value anticipation). In line with Zhang et al. (2016), the results also indicate that customer value anticipation allows firms to design more successful services and products that meet customer values and expectations. The results indicate that the path between BI capabilities and NSP is mediated by customer value anticipation capacity. These findings imply that a firm that can predict hidden patterns and trends using BI will be able to identify a wide range of elements that contribute to customers' future desires. This will, in turn, facilitate the pursuit of new opportunities discovered by BI systems by proposing more successful new products/services for the market. While there is limited research on the effect of BI capabilities on customers' value anticipation, our result is consistent with several empirical works that find a significant association between BI capabilities and firm performance (Chen & Lin, 2021; Huang et al., 2022). Firm performance is the ultimate goal of developing new products.

Second, the results of this study indicate that BI capabilities are associated with firms' ability to produce unique and meaningful innovative service products (NSP innovativeness) for their customers. This is consistent with the traditional wisdom that product innovation requires fresh perspectives (Caseiro & Coelho, 2019). The results also confirm findings of prior research, which indicated that NSP innovativeness increased NSP performance (Anning-Dorson et al., 2017; Fang, 2008; Oo et al., 2019). Our results indicate that the path between BI capabilities and NSP is also mediated by NSP innovativeness. These findings imply that firms that possess BI capabilities have the potential to predict many hidden patterns and trends and offer new insights that contribute to the development of successful innovative products. They also enable firms to search, acquire, analyse and transform data to identify opportunities and challenges in business practices, which makes them more innovative in designing new products. This finding is consistent with the general prediction that BI capabilities increase firms' innovativeness (Caseiro & Coelho, 2019; Huang et al., 2022).

Third, the results reveal that BI capabilities are related to the ability to move quickly from ideas to actual products in the marketplace (speed to market). This finding is consistent with the findings of Alzghoul et al. (2022) and Khaddam et al. (2021). They found that BI capability empowers decision makers with fast access to information and knowledge from diverse sources, allowing them to make timely decisions and providing their organisation with a first-mover advantage. The results also confirm findings of prior research, which showed that NSP speed to market increased NSP performance (Cheng & Yang, 2019; Fang, 2008; Wu et al., 2020, 2017). However, the development of NSP consists of various stages of the decision-making process that usually take a relatively long time. These steps include identifying opportunities or issues, gathering information, formulating alternatives, assessing and valuing options and selecting the best solution. Furthermore, BI can help firms process all these steps in a time-effective manner and gain relevant insights so that they can rapidly transform this into organisational knowledge and actionable decisions. Therefore, BI contributes to the performance of NSP by increasing the speed to market.

Implications

With increasing anecdotal evidence of the contribution of BI systems, many firms are trying to develop their BI capabilities to address rapidly changing environments and to develop more successful products for markets. However, theoretical and empirical evidence on how BI can do this is seemingly absent. In prior research, most of the existing processes describing the contribution of BI capabilities to the performance of NSP are merely conjectures and have not been investigated empirically in terms of a formal theoretical model.

This study contributes to the literature by suggesting and testing a conceptual model describing how BI capabilities could enhance NSP performance instead of relying on the prevailing anecdotal evidence. The suggested model proposes that BI capabilities are dynamic and benefit firms' capacity to anticipate future customer value and enhance both NSP innovativeness and speed to market. Our model shows that the success of NSP is a function of BI capabilities through developing customer value anticipation, NSP innovativeness and speed to market capacities. The contribution of BI capabilities to capacity could, in turn, improve the performance of NSP. By enabling timely and accurate identification of customer values, BI strategic and BI operational capabilities are both dynamic, increasing NSP performance.

Moreover, this study examined the suggested model in the context of Arab countries, particularly Egypt. Limited evidence is available in the existing literature on the impact of BI systems on product and firm performance in such contexts. Some studies reported that many firms in the Arab world encounter cultural obstacles and even failure while attempting to transfer information technology created abroad into practice at home. Our results confirm the role of BI technologies in driving firms' dynamic capabilities to produce successful NSPs in the Arab context.

From a practical point of view, managers need to view investment in BI systems as an important strategic decision that will impact their firm's success in producing new products. We suggest that managers assessing investing in BI should not only look into the ultimate goals of BI but also consider how BI could facilitate and enhance the environment and lead to better NSP performance. Our study shows that BI capabilities contribute to important antecedents of NSP performance. Moreover, decision makers should be interested in conditions that facilitate the contribution of BI capabilities to these antecedents' processes, leading to a better performance of NSP. Our results indicate that the impact of BI capabilities is mediated by its ability to produce more capacity to predict customers' values, increase NSP innovativeness and increase NSP speed to market. This implies that BI capabilities will not lead to desired outcomes unless they facilitate these capacities.

Limitations and future research

There are a few limitations that should be considered when interpreting the findings of this research. First, this is correlational research and relies on perceptual data. Results from comparing the outcomes before and after the implementation of BI could provide more accurate evidence of the contribution of BI capabilities to the performance of NSP. Second, data were collected from a single sector; collecting data from multiple contexts would increase the acceptability of the study's findings. Third, this research did not consider contingencies that facilitate the contribution of BI capabilities to the performance of NSP and its antecedents. Future research should focus more on these contingencies. Finally, we recommend including Pi-shaped skills in future research given the intricate nature of BI analytics—new product innovation linkage (Elayan et al., 2022; Hayajneh et al., 2022).

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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