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Factors Influencing Big Data Analytics Integration in New Product Development: Evidence from Saudi Arabia

Tala Althinayyan [1,2]   Wafi Albalawi [2]

[1] Department of Management Information Systems, College of Business and Economics, Qassim University • Saudi Arabia

t.althinayyan@qu.edu.sa

[2] Department of Management Information Systems, College of Business, King Saud University • Saudi Arabia

walbalawi@ksu.edu.sa

Abstract:

Big data analytics (BDA) have long been used to harness the benefits of the ever-growing volumes of data generated in today's markets. While BDA is usually utilized to inform business decisions and strategies, efforts to incorporate big data analytics into more innovative business functions are rarely explored. This paper investigates the factors that influence the integration of Big Data Analytics tools into the New product development process by surveying 146 product development specialists working in Saudi-based businesses. Our data were analyzed using a Backward Stepwise logistic regression. Our model explained about 28% of the variance in deploying BDA in new product development projects. The model's positive predictive value was 83.7%, and its negative predictive value was 60%, indicating high accuracy in predicting deployment and non-deployment outcomes. Our findings revealed compatibility and top management support as the most significant factors influencing the integration of BDA into product development in Saudi businesses. This study contributes to the body of literature by using a holistic approach to examine the integration of IT solutions into specific business functions. It also guides managers aiming to incorporate Big Data Analytics into their New Product Development projects.

Keywords: Big Data Analytics, New Product Development, Product Management, Technology-Organization-Environment Framework, Diffusion of Innovation Theory.

1. Introduction

Given today's markets' intensely competitive, rapidly changing, and global nature, the ability to innovate and develop products is vital for businesses' survival and growth (Paczkowski, 2020; Schilke, 2014). Big Data Analytics (hereafter BDA) has emerged as a powerful instrument to guide and enhance the new product development (NPD) process since it allows businesses to collect and process data in a timely manner (Del Vecchio et al., 2023). BDA refers to the practice of using mathematical and statistical tools to recognize patterns, detect anomalies, and generate knowledge from vast amounts of data (Sekli & De La Vega, 2021).

Data-driven product development projects assist firms in making informed choices, identifying customer requirements, assessing business prospects, refining innovation procedures, and enhancing innovation outcomes (Del Vecchio et al., 2023). Under the current context of accelerating change, BDA tools are no longer a luxury but a necessity for product development teams (Wang & Zhang, 2020).

Existing research has explored the role and impact BDA plays when successfully integrated in the early stages of the NPD process (Ali et al., 2021). In addition to increasing the probability of new product success (Shirazi et al., 2022) and accelerating the speed of NPD projects (Tan and Zhan, 2017), embedding the NPD process with BDA brings new opportunities as these tools allow businesses to capture customers' unrecognized needs and reduce market-related uncertainties (Zhan et al., 2018). Nonetheless, the impact of these benefits varies significantly across diverse settings (Wang and Zhang, 2020).

While prior studies have substantiated the influence of BDA on firms' innovation performance (Wang and Zhang, 2020) (Cheng & Shiu, 2023), empirical evidence about the drivers behind the decision to employ BDA in NPD projects is still lacking.

In addition, driven by its 2030 Vision, Saudi Arabia is transforming into a knowledge-based economy in which technology and innovation are key pillars (Nurunnabi, 2017). According to Abanumay and Mezghani (2022), 57% of Saudi-based IT leaders felt that big data applications had given their organizations an edge over competitors. Despite BDA's ample benefits, its integration in NPD projects in Saudi-based businesses remains limited.

This paper addresses this gap by empirically examining the factors that impact the integration of BDA tools in the NPD process in developing economies, with a specific focus on Saudi Arabia. Given the unique contextual characteristics of the country's culture, regulations, and market dynamics, precisely identifying drivers relevant to the kingdom's context is needed to understand factors impacting priorities and challenges associated with integrating BDA in the NPD process. Our research delves into the technological, environmental, and organizational factors that could facilitate or impede BDA diffusion within Saudi-based businesses.

The research question guiding this study is:

RQ: What key technological, organizational, and environmental factors influence firms' decision to integrate big data analytics into their new product development processes?

We hypothesize that enacting insights from BDA in NPD involves uncertainty as firms must navigate challenges across technological capabilities, resource availability, and external dynamics. Answering our research question would help other researchers produce more nuanced studies comparing the results of different countries, industries, or specific BDA tools.

This study makes a notable contribution to the existing literature by utilizing a quantitative methodology that has seen limited application in this specific domain. The findings of this work have the potential to further deepen our understanding of the process by which BDA tools are successfully integrated into particular business functions (in our case, NPD), thereby guiding practical technology implementation and assimilation efforts.

The remainder of this paper is organized as follows. Section 2 presents a brief overview of the NPD process and how it can benefit from BDA. In Section 3, we illustrate the research model and develop our hypotheses. Section 4 describes the research method. The results are reported in Section 5. Section 6 discusses the study's findings and their implications. Section 7 concludes this paper.

2. Overview

This section seeks to provide an overview of the current body of knowledge regarding applications of BDA in NPD.

2.1. The NPD process

Cooper (1994) defined the process of product development (PD) as "a formal blueprint, roadmap, template or thought-process for driving a new product project from the idea stage through to market launch and beyond." NPD projects are comprised of several sequential and interconnected stages (Wang & Zhang, 2020).

While elaborate designs and available technology can stall the process at times, NPD projects typically follow a basic pattern common in research and practice. Paczkowski (2020) outlined five primary stages in the NPD process: ideation, development, testing, launch, and tracking. Each step includes several specific NPD tasks. During the idea generation stage, the development team works to identify new opportunities, novel ideas, and product concepts (Cooper, 2014). While many ideas are generated in this stage, only good ones are carried through to the next phase (Christensen et al., 2017). During the product development stage, customers' needs and wants are captured directly through traditional or web-based market research (Schaarschmidt & Kilian, 2014). Resulting insights translate into rough prototypes and initial production models. Some scholars suggest prefacing the development stage with a business analysis process in which the team assesses the targeted market, its competition dynamics, and financial requirements (Wang & Zhang, 2020). During the testing stage, a sample drawn from the target consumer base uses and provides feedback on the product in its initial form. Consumer feedback helps shape and improve the product before introducing it into the market (Schaarschmidt & Kilian, 2014). During the launch stage, the development team works on the product's production and commercialization (Cooper & Kleinschmidt, 1986). The tracking process concerns managing the flow of product information to the appropriate parties throughout the product lifecycle (Kiritsis et al., 2003). These stages, while distinct, create a feedback loop where insights gained in later stages can inform earlier ones or restore the whole project (Paczkowski, 2020).

Among various business processes, product development can be vital for businesses' survival in highly competitive markets (Paczkowski, 2020). While some projects may not follow all stages in sequence due to their unique circumstances and objectives, the pace of change in today's markets necessitates making NPD projects shorter, faster, and more evidence-driven (Ali et al., 2021; Dodson et al., 2014). Information-guided agility is necessary since businesses that fail to deliver suitable products without delay risk losing their market position. (Paczkowski, 2020). Traditionally, product development projects relied mainly on a mix of market research, expert opinion, and experimentation, with uncertainty pervading the process and product success being unpredictable (Ding & Eliashberg, 2002). In today's environment, companies must enhance their capabilities to identify customer wants, translate them into product requirements, quickly develop and test new design concepts, and deliver resulting products in a timely manner (Dodson et al., 2014).

2.2.The BDA Embedded NPD Process

Incorporating BDA can revolutionize the NPD process, potentially lowering risks and providing deeper insights to inform PD projects (Zhan et al., 2018). Shirazi et al. (2022) echoed this sentiment, arguing that businesses' BDA capabilities can increase the success rate of new products.

While still emerging, BDA enables a transformational growth trajectory for organizations seeking to surge past the limitations of established systems (Zhan et al., 2018). Despite the potential advantages of BDA, its integration into NPD is not without challenges. Mikalef et al. (2018) and Almeida (2018) agreed that building an information-driven organizational culture is necessary for leveraging BDA. Others, including Sekli and De La Vega (2021), argued that successfully integrating BDA insights into NPD requires substantial changes in business processes and organizational culture, which is often met with resistance from within the organization.

2.3. Previous Work

While the existing research on the topic of BDA in NPD is still limited (Del Vecchio et al., 2023), the literature provides ample evidence demonstrating BDA's significant potential. Wang and Zhang (2020) examined how BDA can increase sustainable innovation performance. They compared the effect of BDA across three nations: the US, the UK, and Australia. Their study revealed differences across countries regarding which stages of the innovation process were most improved by using BDA as reflected in performance indicators. In addition to identifying stages in which the utilization of BDA did not increase sales growth nor gross margin (i.e., commercialization).

Tan and Zhan (2017) noted how tapping into the knowledge afforded by BD enables businesses to design better products, provide customized services, and incorporate market feedback. The paper proposes that three principles, Autonomy, Connection, and Ecosystem (i.e., ACE principles), provide a framework for using BDA to accelerate NPD initiatives. By analyzing three global Chinese companies that have successfully integrated BDA into NPD, the study found that big data can make the NPD process faster, more efficient, and less costly.

Ali et al. (2021) advocated for exploiting big data to increase knowledge in the early phases of NPD. They proposed a systematic and iterative approach to leveraging multiple internal and external data sources. They argued that knowledge extracted from customer feedback, test reports, and usage data can inform the design stage of NPD. The proposed model was informed by the author's experience in the field (i.e., they followed an industry-as-laboratory approach). As indicated by a survey, most specialists from the company under study expressed positive views about the authors' model.

Within the industrial setting, Zhan et al. (2018) demonstrated how available data can be leveraged to develop a deeper understanding of customers. They found that big data can effectively increase customer involvement throughout the NPD process. BDA techniques enabled customers to express unrecognized needs, thereby allowing managers to employ more customer-centric product development approaches.

On a similar note, Shirazi et al. (2022) provided empirical evidence from Iran, demonstrating how BDA, specifically data aggregation and analysis tools, contribute to new product success by increasing customer agility. Customer agility, in this case, refers to a business's ability to respond to customer-based opportunities. According to this study, BDA tools can derive insights from customers' behavior and preferences, increasing the businesses' responsiveness to changing markets.

Table 1 summarizes our analysis of the previous research on embedding BDA into NPD projects.

Table 1. A Comprehensive Summary of Previous Work.

Author	Focus	Methodology	Context	Key Findings
Wang and Zhang (2020)	The sustainability of innovative performance in NPD projects.	Mixed method	USA, UK, and Australia.	Integrating BDA into NPD showed diverse effects on sustainable innovation performance, with variations observed across countries and at different NPD stages.
Tan and Zhan (2017)	The principles of Autonomy, Connection, and Ecosystem (ACE) as DB delopyment framework.	Case study	China	The ACE principles provided a sucsseful framework for using big data to accelerate NPD and reduce costs.
Ali et al. (2021)	Employing BD in early stages of NPD projects.	Mixed method	The Scandinavia region	Integrating BDA increased the value of data by identifying patterns between multiple data sources. Which in tern enhanced design decisions.
Zhan et al. (2018)	Employing BDA to explore customers' unrecognized needs.	Longitudinal case study	China	BDA can significantly enhance new product development by reducing risks and market uncertainties through early-stage market feedback, identifying unrecognized customer

				needs, and enabling quick responses to customer demands.
Shirazi et al. (2022)	The impact of BDA on customer agility and new product success.	Questionnaire	Iran	The effective use of data aggregation and data analysis tools can shape a firm's customer agility, which in turn leads to new product success.

Source: author's name, year, page.

3. Theoretical model

This study assumes that technological, organizational, and environmental factors substantially influence technology deployment decisions in Saudi businesses. Therefore, we attempt to investigate the determinants of BDA integration in NPD projects at the organizational level. Taking Agrawal's (2015) model as a starting point, we made some modifications to better reflect the nuances of our particular context.

Our model is theoretically grounded in two well-established theories: (1) the Technology-Organization-Environment (TOE) framework. (2) the Diffusion of Innovation (DOI) theory. A brief description of each theory is presented below.

3.1.The TOE framework

The TOE framework lays the foundation for this study's research model. Developed by Tornatzky and Fleischer in the early 1990s, the TOE framework proposes that the adoption and integration of new technologies, such as BDA, is influenced by three key contexts: technological, organizational, and environmental. Figure 1 depicts the original TOE framework.

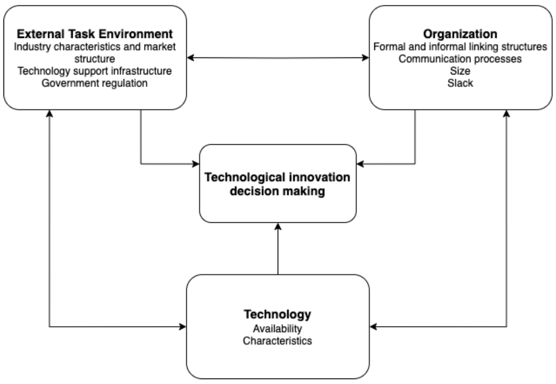

Figure 1: The TOE framework (Source: Arpaci et al. (2012))

However, the TOE framework has been refined many times over the past few years. In this study, the technological context concerns the current state of technology within the organization and alternative technologies available for acquisition. The organizational context refers to the structural and managerial factors that can enable or impede firms from realizing the full benefits of new technologies. The environmental context concerns elements related to the external ecosystem in which the firm exists. This ecosystem includes the organization's industry, competitors, and government (Oliveira & Martins, 2011).

3.2.The DOI Theory

The diffusion of innovation theory was first introduced by Rogers in 1962. The theory sheds light on the process of innovation diffusion by exploring how innovations spread, the reasons behind their diffusion, and the speed at which they are adopted. According to DOI, technology adoption is greatly influenced by the perception of technology. DOI provides a theoretical foundation for understanding the decision and the process of adopting new technologies at both the organizational and individual levels (Oliveira & Martins, 2011). The DOI theory is presented in Figure 2.

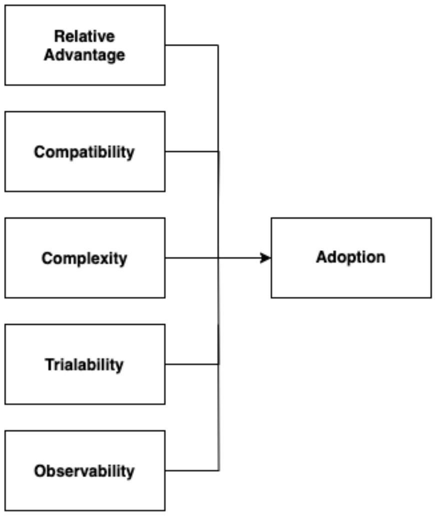

Figure 2: The DOI theory

3.3.A Unified TOE-DOI Approach

Combining IT adoption theories (i.e., the DOI) with the TOE framework has been a well-established practice in IS research for many years (e.g., Amini & Bakri (2015), Chiu et al. (2017), Usman et al. (2019), and Lutfi et al. (2023)). This long-standing convention is rooted in the complementary nature of these two frameworks. While the TOE framework broadly examines technology adoption from three contexts (technological, organizational, and environmental), the DOI further investigates variables relating to the adopted technology (Oliveira & Martins, 2011). Blending these two frameworks provides a holistic, multi-dimensional perspective on what drives technology adoption at the organizational level. This combination allows for a deeper, more robust exploration of a wide range of interconnected variables, including the qualities of the technology itself, the organization's characteristics, and the environment in which it operates (Lutfi et al., 2023). Understanding these internal and external factors in a more nuanced way would ultimately lead to more effective strategies and improved outcomes in technology implementation (Oliveira & Martins, 2011).

4. Theory Development

Our model represents a synchronization of the TOE theoretical framework and the DOI theory. It depicts our attempt to understand the factors influencing BDA integration into the NPD process from technological, organizational, and environmental perspectives. Figure 3 displays the theoretical framework graphically.

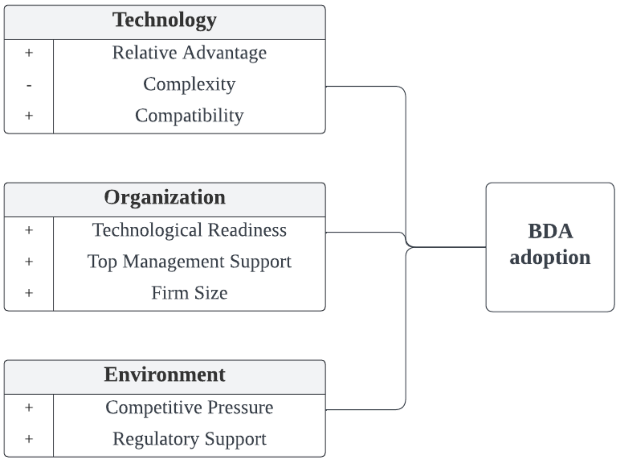

Figure 3: Theoretical framework

4.1. Technological Context

The technological dimension describes the characteristics of the technology being adopted. Within the technological context, the first construct proposed to affect businesses' determination to embrace BDA is relative advantage, which we define as the perceived benefits of adopting a new technology (Lutfi et al., 2022). According to Zhan et al. (2018), businesses are more willing to invest in new technology if they recognize it can provide helpful insights. However, Agrawal’s (2015) investigation showed that relative advantage, as a factor, did not impact organizations' decisions to adopt novel technologies. Therefore, we hypothesize that:

H1: Relative advantage will positively influence BDA integration into NPD.

The next proposed technological construct influencing businesses' decisions is complexity, which we define as the extent to which an innovation is perceived to be challenging to understand and apply (Rogers, 2003). BDA solutions offer the ability to gain instant insight into the market. However, adopting a technological tool can be challenging for businesses that lack technological expertise and capabilities. Prior literature has suggested that innovation complexity impedes adoption (Sahin, 2006). In contrast, a number of existing investigations (including Agrawal (2015) and Gökalp et al. (2022)) revealed that complexity had little, if any, impact on the decision to adopt new technologies. Therefore, we hypothesize that:

H2: Complexity will negatively influence BDA integration into NPD.

On a similar note, compatibility is a crucial technology-related issue. We defined compatibility as the degree to which an innovation can be assimilated with organizational values, business processes, and practices (Rogers, 2003). Research has shown that the perceived ease of integration positively correlates with the likelihood of adoption for businesses. According to Oliveira et al. (2014), the more easily a new technology can be incorporated into an organization's existing systems and workflows, the higher the probability that the business will decide to adopt that technology. Hence, we hypothesize that:

H3: Compatibility will positively influence BDA integration into NPD.

4.2. Organiztional Context

BDA deployment requires businesses to transform their culture into one that accepts BDA. This transformation presents challenges and requires organizations to plan the assimilation process carefully. Prior research has identified insufficient technological capabilities as a primary cause of IT project failures (Jeyaraj et al., 2006). To ensure the successful adoption of new technology, organizations must possess certain requirements, including robust IT infrastructure and capable personnel in IT and management, in addition to other intangible IT-enabling resources such as technological knowledge (Agrawal, 2015). Interstingly, Alaskar et al. (2021) found that organizational readiness (including technological readiness) did not impact new technology implementation. Therefore, we hypothesize that:

H4: Technological readiness will positively influence BDA integration into NPD.

The research on technology adoption offers insights into the importance of top management commitment to the success of IT projects, especially at the organizational level (Jeyaraj et al., 2006). In their paper, Jeyaraj et al. (2006) found top management's support to be a consistent indicator of companies' ability to adopt novel technological solutions. Top management support entails creating a supportive environment where required resources are available to facilitate technology assimilation (Lutfi et al., 2022). Top management support is of greater significance when multiple departments are involved in one project (Jang et al., 2019).

In the case of augmenting NPD projects with BDA insights, several departments need to work together to produce useful market insights. Thus, we hypothesize that:

H5: Top management support will positively influence BDA integration into NPD.

The last construct in the organizational context is organizational size, routinely measured by the number of employees working in the firm. An extended review conducted by Jeyaraj et al. (2006) found that organizational size serves as an excellent indicator of IT adoption in the literature. Small organizations are expected to face financial challenges when assimilating BDA tools.

While large organizations typically possess the resources required to obtain and successfully integrate BDA, they still need to overcome the challenges of coordinating between several departments (Walker & Brown, 2019). However, the relationship between organizational size and IT adoption has been inconclusive, with some studies (e.g., Mwemezi & Mandari (2024)) revealing insignificant findings. Consequently, we hypothesize that:

H6: The organizational size will positively influence BDA integration into NPD.

4.3. Environmental context

Within this context, the first factor exerting force over the organization is the market itself. Competitive pressure refers to the amount of influence competitors in the market have on a company.

In this study, it is described as the degree to which an organization feels challenged or pushed by other players to make technology-related decisions. It focuses on the effect and force of competing firms in the marketplace (Oliveira & Martins, 2011). Previous studies have reported conflicting findings on whether competitive pressure facilitates or impedes organizations' adoption of new technologies (examples include: Kwarteng et al (2024) and Maroufkhani et al. (2020)). This lack of consensus underscores the need for further investigation into the role of competitive pressure. As such, we hypothesize that:

H7: Competitive pressure will positively influence BDA integration into NPD.

Regulatory support is another environmental construct that significantly influences technology deployment decisions (Jeyaraj et al., 2006). While government funds and financial assistance can encourage organizations to embrace innovative technologies, other forms of government regulations, including laws, policies, and standards, may also restrict the market's ability to adopt new technologies (Walker & Brown, 2019). While some studies have found regulatory support to influence the adoption of new technologies by organizations positively (e.g., Lai et al. (2018)), other studies have reported conflicting findings where regulations were not a driver of technology adoption decisions (e.g., Maroufkhani et al. (2020)).

As such, we hypothesize that:

H8: Regulatory support will positively influence BDA integration into NPD.

5. Methodology

In order to empirically test our eight research hypotheses, we delivered a web-based questionnaire to a sample of Saudi-based companies .

The primary construct measures were borrowed from existing assessment tools. Minor adaptations were made as needed for contextualization, but the core items and constructs remained unchanged. Items for Technological readiness, Competitive Pressure, and Regulatory Support were adapted from Agrawal (2015).

The measures for Relative Advantage were adapted from Ghobakhloo et al. (2011). Four items pertaining to Complexity were adapted from Alaskar et al. (2021). Items assessing Compatibility were drawn from Agrawal (2015), Alaskar et al. (2021), and Karuga (2019). Organizational size was measured using items borrowed from Agrawal (2015) and Karuga (2019). Items for Top Management Support were drawn from Alaskar et al. (2021) and Oliveira et al. (2014). The questionnaire was translated into Arabic and reviewed by a panel of four academics to ensure the accuracy and clarity of the questions. All variables were measured using a five-point Likert scale, ranging from strongly agree to strongly disagree. The dichotomous dependent variable, deployment, measured -with a yes/no question- whether or not the respondents' firms have assimilated BDA tools. In the questionnaire's introduction, participants were informed about the study's objectives and assured that their responses would be treated with strict confidentiality .

The sampling method employed in this study was non-probability convenience sampling, which involves selecting respondents based on their accessibility to researchers rather than using random selection techniques. This method is appropriate as our target population of experts is relatively small and hard to reach (AlGahtani, 2016).

The data-gathering process was conducted in November 2023. Our questionnaire was administered through SurveyMonkey, a web-based survey tool. Appendix A contains the questionnaire through which responses were collected. We targeted professionals directly involved in their companies' product development projects, including product managers, product developers, product designers, and other individuals in comparable roles. Participants were contacted through their professional social networks (LinkedIn and WhatsApp), informed of the scope and purpose of the research, and asked to participate. Data collection lasted approximately two weeks. After collecting responses, incomplete responses were excluded.

A final sample of 146 observations was considered sufficient, as per Laerd Statistics (2017) guidance who suggested using a sample size of at least 15 cases for each parameter considered in the measurement instrument. Table 2 describes the demographic characteristics of the respondents in this study and information about their firms.

Table 2. Sample profile

Profile of respondents	**Number**	**%**
Respondents’ Position :		
Product manager*	78	53.42
Product developer*	54	36.99
Product designer*	14	9.59
Firm size :		
Micro (1 - 5 employees)	4	2.74
Small (5 - 49 employees)	16	10.96
Medium (50 - 249 employees)	36	24.66
Large (250+ employees)	90	61.64
Firm location :		
Central Region	132	90.41

Eastern Region	3	2.05
Western Region	10	6.85
Northern Region	1	0.68
Southern Region	0	0.00
Total	146	100

* And persons of equivalent position

Source: author’s name, year, page.

6. Results

Prior to data analysis, the reliability of the measurements was assessed using Cronbach's α coefficient. While a threshold of 0.7 or higher is typically preferred for internal consistency reliability, a coefficient of 0.5 or above can still be considered acceptable. As shown in Table 3, three constructs had a Cronbach's α coefficient of 0.6, indicating moderate reliability (Hinton et al., 2004). The other constructs exceeded 0.7, demonstrating reliable measurement.

Table 3. Cronbach's Alphas for questionnaire items.

Construct	No. of items	α coefficient
Relative advantage (RA)	4	0.78
Complexity (CL)	3	0.70
Compatibility (CM)	3	0.60
Technological readiness (TR)	3	0.81
Top Management Support (TMS)	4	0.85
Firm Size (FS)	2	0.80
Competitive Pressure (CP)	2	0.62
Regulatory Support (RS)	2	0.60

Source: author’s name, year, page.

Logistic regression is specifically designed to analyze situations where the outcome variable is dichotomous (Kleinbaum & Klein, 2010). It proves especially useful when estimating the probability of a particular event (Kleinbaum & Klein, 2010), such as the successful deployment of IT solutions, based on the values of one or more predictor variables. Despite its susceptibility to multicollinearity issues, logistic regression was deemed an appropriate technique. Our data did not suggest any problematic multicollinearity according to the diagnostic testing procedure, reinforcing the reliability of logistic regression.

A Backward Stepwise (Likelihood Ratio) logistic regression was used to determine the effects of our eight variables on the likelihood of BDA deployment. The variables were selected for the final model in a step-by-step process based on their p-values. A p-value threshold of 0.05 was used as a cut-off, limiting the number of variables included in the model. The Box-Tidwell (1962) procedure was used to evaluate the linearity of the continuous variables in relation to the logit of the dependent variable. By applying the Bonferroni correction across all terms included in the model, the threshold for statistical significance was adjusted. As a result, only p-values less than 0.0029 are considered significant (Tabachnick & Fidell, 2014).

This assessment found that all continuous independent variables had a linear relationship with the logit of the dependent variable. There were four cases with standardized residuals below -2 standard deviations, all of which were kept in the analysis as they were above the -2.5 threshold and are considered important given our small sample size. The logistic regression model was statistically significant, $\chi2(8) = 27.574$, $p < .001$. The model explained 28.2% (Nagelkerke R2) of the variance in the deployment decision and accurately classified 81.2% of cases. Sensitivity reached 94.5%, specificity was at 31%, positive predictive value was at 83.7%, and negative predictive value was at 60%. Our analysis shows that two factors most influenced the integration of BDA: Compatibility and Top Management Support (See Table 4 and Table 5).

Table 4. Logistic Regression Predicting the Likelihood of BDA adoption based on RA, CL, CM, TR, TMS, FS, CP, and RS.

	B	SE	Wald	df	p	Odds Ratio	95% CI for Odds Ratio	
							Lower	Upper
CM	1.035	0.368	7.898	1	0.005	2.815	1.368	5.794
TMS	0.839	0.345	5.905	1	0.015	2.313	1.176	4.549
Constant	-5.029	1.360	13.676	1	<.001	.007		

Source: author's name, year, page.

Table 5. Results Summary Table.

Hypothesis	**Decision**
H1	Unsupported
H2	Unsupported
H3	Supported
H4	Unsupported
H5	Supported
H6	Unsupported
H7	Unsupported
H8	Unsupported

Source: author's name, year, page.

7. Discussion

7.1. Technological factors

The results of the study demonstrate that among the technology-related determinants of BDA integration, compatibility (H3) was found to have a positive significant effect on a firm's decision to embed BDA tools into their NPD practices. Firms appeared more inclined to embrace BDA if it meshes with their existing working processes and does not require substantial changes to existing IT systems. According to Alaskar et al. (2021), characteristics of how well BDA fits within the firm's current practices outweigh adoption difficulties and readiness issues. Given the complexity of modern systems, ensuring compatibility is paramount. Incompatibility can trigger severe disruptions and data loss, potentially leading to financial and legal repercussions. This concern is particularly critical for Saudi-based businesses, as data regulations in the country are strict, and any violations could have grave consequences. This result is consistent with previous studies, including Agrawal (2015), Alaskar et al. (2021), and Gökalp et al. (2022).

Relative Advantage (H1) does not significantly influence a firm's decision to integrate BDA tools. One potential explanation for the insignificant effect is that PD departments may struggle to understand how BDA could benefit their operations. In our case, most respondents belonged to organizations where marketing is not the primary area of operation. Consequently, they may lack familiarity with the advantages of traditional marketing analysis techniques, let alone more advanced technologies like BDA. This finding is consistent with the earlier finding of Agrawal (2015), who found that while insignificant, Relative Advantage was perceived to have a considerable influence on BDA integration decisions.

Similarly, Complexity (H2) did not emerge as an important factor influencing BDA integration decisions. This result may be because large Saudi firms (which constitute the majority of our sample) are usually technology-oriented and willing to adopt complex solutions if the benefits are clear. Additionally, BDA solutions have become increasingly user-friendly with intuitive interfaces and accessible learning resources, which lessen the impact of perceived complexity. These results are consistent with the extant research findings regarding the diminishing impact of complexity on DBA integration (Agrawal, 2015).

7.2.Organizational factors

Top management support (H5) was found to influence the integration of BDA significantly. This finding entails that top management's support and involvement in the process of assimilating BDA tools into the PD process plays a crucial role in ensuring its success. As leaders, managers can allocate the necessary funding and resources. Their support can also facilitate acceptance of changes as employees would feel more comfortable embracing novel technologies like BDA. This holds greater significance in cases where organizations have only recently adopted BDA tools into their operations. Although we did not collect data specifically on the deployment timeline, we can reasonably assume that BDA adoption is still in its relatively early stages across PD departments in Saudi Arabia, given the country's recent initiation of digital transformation efforts. Prior research has repeatedly shown that top management support is critical to BDA assimilation (Agrawal, 2015; Alaskar et al., 2021).

Technological readiness (H4) did not emerge as an important determinant of BDA adoption in this study. The results may be explained by the fact that 61% of our respondents belong to large firms. Large Saudi firms typically have quite advanced technological capabilities and expertise, hence lessening the weight of this factor against other contextual considerations. Similarly, since these firms have the financial capacity to overcome the lack of technological capabilities through extensive training and capacity-building efforts. This result aligns with Agrawal's (2015) and Alaskar et al.'s (2021) findings.

Firm size (H6) is another organizational factor that does not impact BDA deployment. This may be attributed to the fact that BDA tools range in scale and capabilities and are almost always scalable to serve organizational needs. Therefore, our respondents did not perceive their organization's size as a critical issue in BDA implementation. Another plausible explanation is that our unbalanced sample may have caused this result. This result was calibrated by Mwemezi & Mandari (2024), who found that management support and financial capital, rather than firm size, had a more significant impact on BDA adoption in Tanzanian banks.

7.3. Environmental factors:

Our findings indicate that both variables in the environmental context (Competitive pressure (H7) and regulatory support (H8)) do not impact the BDA integration rate. It is possible that since most of the respondents belonged to large firms, they may not perceive competition as a driving factor to assimilate DBA since they do not face direct competition from rivals of comparable size in their domestic market. While Saudi regulations promoting data utilization could boost BDA integration, in practice, many remain broad frameworks with compliance and incentives being introduced gradually. These findings are consistent with those of (Maroufkhani et al., 2020).

8. Theoretical and practical implications

8.1. Theoretical implications

The success of BDA tools depends not only on their capabilities but also on how they assimilate within the overall organizational environment. This research builds on this assumption and makes several theoretical contributions. First, our study leveraged comprehensive models, which are not only well-established but also provide a robust, multifaceted understanding of BDA adoption within specific business functions (i.e., product development departments). Second, while the existing literature favors mixed-method designs, our study contributes a purely quantitative perspective. Thirdly, we extended this research arena beyond its previous focus on advanced economies as our work breaks new ground by investigating these dynamics in the Saudi Arabian setting. Finally, our findings revealed that top management support and compatibility were the sole determinants of BDA assimilation within NPD projects. This may be surprising, especially given the impact other internal and external factors usually play in IT deployment projects.

8.2. Practical implications

For decision-makers considering BDA initiatives, our findings provide a sound basis for determining the most influential factors in increasing the success of such efforts. Specifically, firms can evaluate the compatibility of BDA tools before fully assimilating them into PD projects. We have also highlighted the importance of informing and involving top management from the early stages of BDA integration. Our research demonstrates the benefits and potential significant improvements that can be achieved by using BDA insights to inform PD decisions, guiding them beyond market-based, reactive forms of development and more toward active, predictive PD strategy.

9. Conclusion

BDA tools are crucial in helping business functions strengthen and evolve their operations to thrive within today's dynamic markets. Nonetheless, their deployment may require major modifications in the existing business processes.

While the rate of BDA adoption has increased rapidly in Saudi Arabia in recent years, relatively limited empirical research has been conducted to analyze exactly how these solutions are being assimilated across different organizational functions. This study sought to identify the impact of innovation characteristics and technological, organizational, and environmental factors on BDA integration into NPD projects. Our research model was drawn from the TOE framework and the DOI theory. We evaluated the model using a sample of 146 PD specialists in Saudi Arabia. Through our analyses, we have successfully answered the core research question underlying this work. Our results indicated that compatibility and top management support directly affect firms' decisions to integrate BDA into NPD effectively. These findings provide valuable insights to managers and policy-makers in Saudi Arabia and neighboring regions. While this paper contributes to understanding factors influencing BDA assimilation, some limitations must be acknowledged. First, our paper examined the problem solely through the lenses of a unified TOE-DOI framework. Future studies could incorporate models retaining PD to gain more profound knowledge about how BDA tools and strategies could be optimally leveraged in PD practices. Second, our sample size was relatively small and skewed towards larger firms, which could have impacted the results. With a larger, more balanced sample capturing responses from a broader range of businesses, some factors may vary in strength or significance. Finally, the explanation of BDA integration was very general and broadly defined. The concept was introduced to respondents in such a way that most respondents affirmed they were utilizing insights from BDA to inform PD decisions. We probably would get a more precise view of the issue with more narrowly defined BDA tools across specific PD stages. Further investigating these constraints can help develop an even more robust comprehension of the drivers influencing BDA assimilation success in core business operations.

Appendix A

Variable	Items	source
Technological Context		
Relative Advantage	1- Big Data Analytics provides new opportunities. 2- Big Data Analytics allows us to enhance our productivity. 3- Big Data Analytics provides timely information for decision-making purposes. 4- Big Data Analytics technology increases our profitability.	(Ghobakhlooet, 2011)
Complexity	1- The use of Big Data Analytics requires a lot of mental effort. 2- The use of Big Data Analytics is frustrating. 3- Big Data Analytics is too complex for our firm to use. 4- The skills needed to use Big Data Analytics is too complex for us.	(Alaskar et al., 2021)
Compatibility	1- Existing beliefs/values of my organization are consistent with the changes introduced by big data analytics technology. 2- My organization possesses the infrastructure necessary to enable adoption of big data analytics to drive New Product Development. 3- Overall, it is easy to incorporate Big Data Analytics into our New Product Development practices.	(Agrawal, 2015) (Alaskar et al., 2021) (Karuga, 2019)
Organizational Context		
Technological readiness	1- IT infrastructure of my organization is available to support Big Data Analytics related applications. 2- My organization is committed in ensuring that employees are familiar with Big Data Analytics technologies. 3- My organization has a sound knowledge of Big Data Analytics technologies.	(Agrawal, 2015)
Organizational Size	1- Total capital of my organization is more compared to the industry. 2- Returns of my organization are high compared to the industry. 3- Our organization has competent staff that can drive the adoption of technologies such as big data analytics.	(Agrawal, 2015) (Karuga, 2019)
Absorptive Capacity	1- My organization is likely to invest funds in Big Data Analytics technologies. 2- My organization has prior knowledge and experience with related technologies.	(Agrawal, 2015)

	3- My organization is likely to be interested in assimilating the Big Data Analytics technologies in order to gain competitive advantage. 4- My organization is likely to consider the assimilation of the Big Data Analytics technologies as strategically important.	
Top Management Support	1- The company's management provides resources necessary for the adoption of Big Data Analytics. 2- The company's management supports the adoption of Big Data Analytics. 3- The company's management provides strong leadership and engages in the process when it comes to information systems. 4- The company's management is willing to take risks (financial and organizational) involved in the adoption of Big Data Analytics.	(Alaskar et al., 2021) (Oliveira et al., 2014)
Environmental Context		
Competition Intensity	1- My organization experienced competition intensity to implement Big Data Analytics technology. 2- My organization would have faced competitive disadvantage if Big Data Analytics technology had not been adopted.	(Agrawal, 2015)
Regulatory Support	1- The use of Big Data Analytics technologies is driven by the government influence. 2- Standards/laws support adoption of Big Data Analytics technologies. 3- Adequate legal protection supports post-Big Data Analytics technology adoption.	

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