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ORIGINAL RESEARCH

# How can big data and predictive analytics impact the performance and competitive advantage of the food waste and recycling industry?

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**Abstract**
Big data and predictive analytics (BDPA) techniques have been deployed in several areas of research to enhance individuals' quality of living and business performance. The emergence of big data has made recycling and waste management easier and more efficient. The growth in worldwide food waste has led to vital economic, social, and environmental effects, and has gained the interest of researchers. Although previous studies have explored the influence of big data on industrial performance, this issue has not been explored in the context of recycling and waste management in the food industry. In addition, no studies have explored the influence of BDPA on the performance and competitive advantage of the food waste and the recycling industry. Specifically, the impact of big data on environmental and economic performance has received little attention. This research develops a new model based on the resource-based view, technology-organization-environment, and human organization technology theories to address the gap in this research area. Partial least squares structural equation modeling is used to analyze the data. The findings reveal that both the human factor, represented by employee knowledge, and environmental factor, represented by competitive pressure, are essential drivers for evaluating the BDPA adoption by waste and recycling organizations. In addition, the impact of BDPA adoption on competitive advantage, environmental performance, and economic performance are significant. The results indicate that BDPA capability enhances an organization's competitive advantage by enhancing its environmental and economic performance. This study presents decision-makers with important insights into the imperative factors that influence the competitive advantage of food waste and recycling organizations within the market.

**Keywords** Waste and recycling industry · Business performance · Big data and predictive analytics · Decision making · Competitive advantage

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## 1 Introduction

Big Data (BD) is receiving increasing attention in both academic and industrial research (Bresciani et al., 2021; King & Wang, 2021; Poma & Shawwa, 2022; Zhu et al., 2021). BD refers to real-time, complex, and massive data that needs to be analyzed through sophisticated approaches (Li et al., 2022; Muchenje & Seppänen, 2023; Papadopoulos & Balta, 2022; Sumbal et al., 2017; Zhang et al., 2022). Predictive analytics models aim to analyze the available data to provide meaningful predictions (Wang et al., 2016a). Big data and predictive analytics (BDPA) refers to the analytical approaches that entail accessing, retrieving, storing, analyzing, visualizing, and managing huge amounts of complex data, supported by appropriate tools and systems (Dubey et al., 2019; Mishra et al., 2018b). In BDPA, data are gathered from different sources, such as real-time systems, remote sensing tools, and audio-visual sources (Bendre & Thool, 2016). Subsequently, the data are manipulated, cleaned, filtered, and shared online or offline. BD storage requires a large infrastructure in which efficient storage approaches are required to ensure improved data utilization (Shafique et al., 2019). Data analytics techniques are then deployed to extract meaningful information using data mining, computational intelligence, and machine learning. The extracted information and presented visualizations are utilized to provide end-user insights and future directions without the need for specific skills or requirements.

Generally, BDPA could refine decision-making procedures, quality of manufacturing operations, and forecasting performance in any field or industry (Eckstein et al., 2015). BDPA has made researchers interested in investigating industry operations, management, and performance (Aydiner et al., 2019; Matthias et al., 2017) and grand challenges such as climate change (Dwivedi et al., 2022). Previous literature conceptualizes BDPA as a significant capability of an organization that allows it to analyze BD and present business-based insights that enable it to surpass its competitors (Krumeich et al., 2014). Although BD analytics might be considered a research trend, data-driven analytics in business and industry is deeply explored in statistical-based literature and related scientific applications (Zhong et al., 2016). Recently, BDPA approaches are utilized to explore waste management in several industrial areas, such as construction (Jinying Xu et al., 2020) and polymers (Velvizhi et al., 2021).

Industrial enterprises are moving towards more sustainable production and consumption practices and activities (Kabadurmus et al., 2022; Xu & Yeh, 2017). Thus, determining the most appropriate and efficient eco-friendly decisions can be achieved through accurate and reliable data from all related parties in the supply network and by utilizing data science and analysis techniques. If utilized effectively, data science and predictive analysis can be used to derive event-driven, intelligent, and accurate decisions that can be used to design and manage process plans (Kuo et al., 2021). Following the famous story of the Mobro 4000 or Gar-barge in 1987, a continuous concern regarding waste treatment and recycling has become evident (Acuff & Kaffine, 2013). In particular, increasing academic and industrial interests aim to address the cost of waste disposal in societies, provide solutions to landfill constraints, and meet contamination threats. With a specific focus on greenhouse gas emissions, recycling is considered a potential solution to address this upstream externality. Manufacturing from raw materials generates more emissions than recycling. Rapid industrial development and urban expansion radically increase the volume of generated waste, particularly food waste (Yeo et al., 2019).

Following the release of the Sustainable Development Goals (SDGs) in 2015, significant efforts have been made worldwide to respond to economic, political, and environmental blockades (Haas & Ivanovskis, 2022). SDG 12 is linked to the production, management, and consumption patterns of food to address the food waste problem (Jenkins et al., 2022). Food waste is a chief concern among decision makers because of its huge share of overall municipal waste (Murasawa et al., 2013), accounting for 931 million tons of waste annually (Statista, 2021). As an affordable and simple option, landfills are used as the primary approach to waste treatment and disposal (Chao et al., 2016). This has accelerated concerns regarding the harmful impacts of waste, including methane and leachate gases, on the environment. This issue has also raised arguments regarding the best municipal waste treatment and recycling strategies, and controlling the amount of food waste generated and enhancing treatment performance have emerged as essential goals.

When considered for improving organizational performance, BD adoption brings significant benefits to organizations (Raguseo & Vitari, 2018). BDPA adoption has gained increasing attention at the organizational level regarding the anticipated benefits that are reflected by earning a competitive edge in the business (Lutfi et al., 2023; Wessels & Jokonya, 2022). Despite the expected benefits from BD adoption by organizations (Staegemann et al., 2021), the literature indicates that businesses face several barriers to BD adoption. BD adoption by 80% of businesses are subject to failure if not accompanied by appropriate strategic goals (Choi et al., 2022). This leads to low BD adoption among organizations (Nam et al., 2019) and only few organizations succeed in experiencing the anticipated benefits (Almaiah & Nasereddin, 2020).

Despite the increasing interest in deployment and evaluation approaches (Lutfi et al., 2023), few researchers focus on the evaluation of BDPA from decision-makers' perspective. Research on the deployment of BDPA in the context of food waste and recycling management is still lagging because of limited resources and awareness of the basic impediments to BD usage and adoption. In addition, as researchers, decision-makers, and governments become more interested on environmentally friendly practices in industry, there is a call to deploy innovative and up-to-date models to promote this shift.

This study examines how BDPA adoption impacts the performance and competitive advantage of the food waste and recycling industry. The proposed model is based on several theoretical grounds: resource-based view (RBV) (Barney, 1991), technology-organization-environment (TOE) (Tornatzky et al., 1990), and human organization technology (HOT). As RBV suggests that an organization's performance relies on its basic resources (Barney, 1991), it is adopted in this study to explore the impact of BDPA adoption on an organization's performance. Organizational resources can be information, knowledge, and processes, which are represented in the form of tangible or intangible resources (Barney, 1991). In addition, the TOE and HOT models are used to explore the drivers of BDPA adoption at the level of an organization's technology adoption. Through a combination of these theories, we first investigate whether organizational, human, environmental, and technological constructs significantly impact BDPA adoption. In addition, we analyze the relationship between BDPA adoption and the competitive advantage of the food industry through environmental and economic performance.

In summary, this study investigates the impact of BDPA on the performance and competitive advantage of the waste and recycling industry and addresses the following research question:

*What are the potential factors that impact the competitive advantage of organizations in the food waste and recycling industry?*

The remainder of this paper is organized as follows. Section 2 presents the literature review and theoretical background of this study. Section 3 presents the hypotheses development.

Section 4 presents the survey-based approach used in this study, and Sect. 5 presents the data analysis and results. Finally, Sects. 6 and 7 present the discussion and conclusion, respectively.

## 2 Literature review and theoretical background

### 2.1 Literature review

This study explores the effect of BDPA adoption on enterprise performance, focusing on competitive advantage in the food waste and recycling industry. Hence, we review several aspects of the research and incorporate several issues. First, we examine organizations' adoption of innovation and the components that impact this process, focusing on managers' perspectives. Second, this research focuses on BDPA adoption by organizations; hence, it is crucial to explore studies that focus on this issue and the factors explored in previous literature in this context. Third, we explore existing studies on food waste and recycling and how the adoption of technologies, particularly BDPA, is utilized to improve the performance of organizations.

Technology adoption at the organizational level raises a wide group of interrelated variables in the decision-making process (Talapatra et al., 2022). Focusing on organizational behavior, research at the micro level is the center of debate, with variant variables linked to the adoption process. This topic is investigated by focusing on the adoption of decisions at the individual level and its correlation with decision making at the organizational level (Spencer et al., 2012). A resonating debate encloses whether exploring decision making at the individual level is fundamental to analyzing the process at the organizational level. Organizational decision making should address several difficult, interrelated, and diverse variables that go beyond the intellectual capabilities and experiences of decision makers. Hence, the analysis of decision making in this context should be viewed as a web of dynamic interrelated factors. Several factors are identified as drivers of adoption, highlighting the various factors in each study. The main factors tied to adoption are classified as firm- and environment-related variables (Martínez-Román et al., 2020). While firm-related variables focus on an organization's structure and orientation, environment-related variables highlight the power imposed by contextual factors. Firm-related variables include human resources (Mirabolghasemi et al., 2019), knowledge (Mirabolghasemi et al., 2019), organization structure (Irfan, 2020), and size (Mohamed et al., 2009). Contextual factors include competitiveness (Aboelmaged, 2014; Wenjuan Xu et al., 2017), complexity (Gangwar et al., 2015; Kandil et al., 2018), and cooperation. This raises the need for a more in-depth investigation of new and emerging variables that could impact an enterprise's performance and position in the market.

Impelled by BD availability (Yan Zhu et al., 2019), countries, scholars, and enterprises are more willing to share and utilize data (Chauhan et al., 2022). Open BD provides valuable and rich sources for academic and industrial communities, including economic (Souza & Leung, 2021), weather (Cox et al., 2018), transportation (Malik & Zatar, 2020), social network (Singh & Leung, 2020), medical (Shang et al., 2020), and financial data (Morris et al., 2018). As an imperative part of the future of high-tech, BD encourages many stakeholders in the business and industry, aiming to gain enormous benefits (Raguseo, 2018). BD adoption reflects the organizations' desire to deploy innovative strategies to refine their productivity, address any potential risk, meet customer requirements, and design new strategies (Baig et al., 2019). While research on the adoption of technologies is diverse, empirical research on BDPA adoption is less explored (Lei et al., 2021). The adoption focuses on its general concept, without considering a particular technology (Lai et al., 2018; Ram et al., 2019; Verma, 2017; Walker & Brown, 2019). Few studies focus on a particular fold of BDPA, such as social media, predictive, visual, and in-memory analytics software. Several studies utilize conventional adoption models to explore the variables that boost BDPA adoption, revealing and confirming the impact of several factors, such as perceived benefits, ease of use, data quality, compatibility, relative advantage, complexity, security and privacy, and observability, on the adoption process (Kim et al., 2018; Lai et al., 2018; Park & Kim, 2021; Walker & Brown, 2019). Several techniques are utilized to explore these factors, with surveys and interviews being the dominant approaches to collect data (Lei et al., 2021). In addition, research on BDPA targets both individual and organizational levels of adoption, with less focus on the organizational levels, increasing the need for more focus on exploring the variables that impact organizational behavior. Conventional models cannot discover correlations within organizations that have complex structures with steady relations to their surroundings and various aims for the adoption of BDPA tools.

Finally, in the industry context, BDPA has been investigated; although, less focus has been given on waste management and recycling. For example, (Lu, 2019) focuses on identifying illegal waste using BDPA. In addition, Stekelorum et al. (2021) focus on the enhancement of circular economy practices by utilizing BDPA. Wongburi and Park (2021) focus on deploying BDPA for wastewater treatment. However, BDPA adoption in the context of the waste industry, through the evaluation of influential variables at the organizational level, is rarely discussed in the literature.

## 2.2 Theoretical background

### 2.2.1 Resource-based view (RBV)

Resource procurement and deployment play major roles in gaining a competitive edge in the market, which is broadly investigated in several theories, such as forceful capabilities (Teece et al., 1997), resource advantage (Hunt & Morgan, 1995), RBV (Wernerfelt, 1984), and extended RBV (Lavie, 2006). RBV, which is introduced by Barney (1991), has a significant influence on theoretical and empirical research in management areas. RBV influences several fields of research and is cited a considerable number of times (87,682 citations as of May 2022 based on Google Scholar). It presents powerful insights into the impact of inter-organizational resource diversity on an organization's competitive advantage (Ployhart, 2021). Based on RBV, competitive advantage can be achieved through utilizing and integrating nonsubstitutable, inimitable, rare, and valuable resources (Barney, 1986). This indicates that both intangible and tangible resources have particular features in an organizational setting (Nason & Wiklund, 2018). Organizations can advance unique capabilities and allocate rare and unique resources that are organization-oriented and distributed diversely. RBV is utilized to explore organizations' strategic decisions to gain a competitive edge and address the increasing demands of businesses.

RBV investigates managers' utilization of resources to meet sustainable goals. If organizations obtain the required resources, proactive environmental policies can be followed efficiently. These policies should be supported by funding decisions and administrative strategies to address the increasing obstacles. Referring to Barney (1991), sustainable competitive advantage builds on the allocation of an organization's resources that are valuable, rare, inimitable, and non-substitutable. Valuable resources are utilized to employ and explore openings to address risks within an organization's surroundings. Rare resources are usually restricted and may not be evenly allocated to address an organization's existing and possible challenges. Inimitable resources are resources that cannot be replicated by other organizations; they refer to several environmental variables such as causal ambiguity, historical conditions, and social complexity. Finally, non-substitutable resources refer to unreplaceable resources. Hence, we explore the effect of environmental and economic performance on the competitive advantage of organizations within the food waste and recycling industry.

### 2.2.2 Technology-organization-environment (TOE)

We also consider the TOE framework. In this context, the variables that impact an organization's adoption, assessment, and implementation of IT technologies are considered. TOE provides a theoretical basis for exploring contextual variables that are based on particular environmental, organizational, and technological contexts (Ahmadi et al., 2015; Lin, 2014; Yadegaridehkordi et al., 2018). The TOE framework indicates three influential folds of IT usage by an organization: technological, organizational, and environmental (Ahmadi et al., 2017; Asadi et al., 2022). The technological aspect refers to technological features and how the organization perceives them. Organizational aspect refers to the qualities of an organization, including its structure, scope, size, and human resources. Finally, the environmental fold indicates an organization's interactions with the government, partners, and competitors. This dimension is framed within the various activities of an organization linked to its external environment (Lian et al., 2014; Musawa & Wahab, 2012; Yeboah-Boateng & Essandoh, 2014), such as competitive pressure, vendor support, and legal issues.

The TOE framework has robust support from empirical and theoretical studies in the information system (IS) domain. It is deployed broadly to examine the drivers of an organization's adoption of technology in several contexts. For example, Yi-Shun Wang et al. (2016b) investigate the variables that influence the hotel deployment of mobile reservation tools and find that critical mass, technology competence, firm size, and compatibility are the most influential variables. electronic data interchange adoption is investigated in the literature, in which several factors are indicated, including the regulatory environment, IT resources, financial resources, and perceived cost–benefits (Iacovou et al., 1995). Focusing on the e-business context, Hsu et al. (2006) adopt the TOE framework to explore prominent factors in U.S. organizations and confirm the significant impact of the regulatory environment, external pressure, organizational readiness, and perceived benefits on e-business use. In addition, Teo et al. (2009), which focus on the e-procurement context, adopt the TOE framework and indicate that partner influence, information sharing, top management support, firm size, perceived costs, and perceived benefits are the most important factors.

### 2.2.3 Human organization technology (HOT-fit)

Presented by DeLone and McLean (1992), the IS success model indicates that information systems can be assessed based on six quality dimensions: system, information, use, satisfaction, individual effects, and organizational effects. The model is updated by exchanging individual and organizational effects with net benefits and adding a service quality dimension (DeLone & McLean, 2003). Subsequently, the MIT90s framework is presented as an IT-organizational framework to investigate an organization's technology adoption by focusing on management processes, technology, organizational structure, individuals and roles, organizational strategy, and the external environment (Bacsich, 2006). This framework aims to emphasize some essential points for evaluating business performance based on the adopted strategy (Mistry, 2008).

By integrating the IS success model and IT organizational fit model, Maryati Mohd Yusof et al. (2008) present the HOT-Fit framework, which focuses on both human and organizational aspects, for appraising technologies in the health sector. The HOT-fit framework complements the IS success model in classifying the evaluation variables and dimensions and incorporating the organizational dimension in the framework through the "fit" concept among these dimensions (Maryati Mohd Yusof et al., 2008). The HOT framework is based on human, technology, and organizational dimensions to provide a broad view of social, technological, and organizational interactions and relations (Häggström & Lindroos, 2016). Other studies use "Man" instead of "Human" to refer to ergonomics. This framework is used in the literature to broadly evaluate the performance of information systems (Irfan, 2020).

### 2.2.4 Research gap

BD is a critical asset in transforming the way businesses operate (Wamba et al., 2015). More businesses process and use BD to boost performance and compete in the market. Previous research reveals a significant link between the use of BD and organizational performance (Mikalef et al., 2019a; Wamba et al., 2017). Although BDPA impacts business performance and adds value to it, few studies explore how its adoption can add value to business performance (Mikalef et al., 2019a). This issue is not yet explored in recycling and waste management in food industries. In addition, how to implement BDPA in an organization to gain anticipated value is still ambiguous (Lutfi et al., 2023). Mikalef et al. (2019a) indicate that the deployment of BDPA faces several obstacles that hinder value creation. This raises the need to explore the drivers of BDPA adoption in general and in the food recycling and waste industry in particular. In general, research studies that examine BDPA adoption focus less on the post-adoption stage (Munawar et al., 2020). Hence, this study aims to highlight the post-adoption stage of the BDPA in the food recycling and waste industry.

The main theoretical base of this research is the RBV, in which the outsmarting of an organization can be established with the distinct utilization of the organization's resources (Backman et al., 2017). In this context, we focus on BD deployment as an emerging resource with high capabilities. RBV deployment in the context of waste management in food industries is rarely addressed in the literature. In addition, exploring the factors that boost BDPA adoption using a suitable theory is important. Referring to the empirical support, robust literature review, and theoretical perspectives elaborated in the above sections, this study adopts the TOE and HOT-fit frameworks to inspect the factors that influence BDPA adoption. BDPA adoption can be effectively enabled by the features of the organization itself, impacted by environmental factors, and influenced by technological factors.

## 3 Hypotheses development

Referring to the theoretical grounds explained in this study and following the literature review, as presented in Tables 6 and 7 in Appendix A, research hypotheses are developed based on several theories (see Fig. 1). We hypothesize that four dimensions affect an organization's BDA adoption: organization, humans, technology, and environment. Figure 2 illustrates the research model.

In the organization dimension, we consider top management support to be an influential factor in the adoption of new technologies and tools. This factor is investigated and supported by empirical results from many research areas (Alshamaila et al., 2013; Khwaldeh

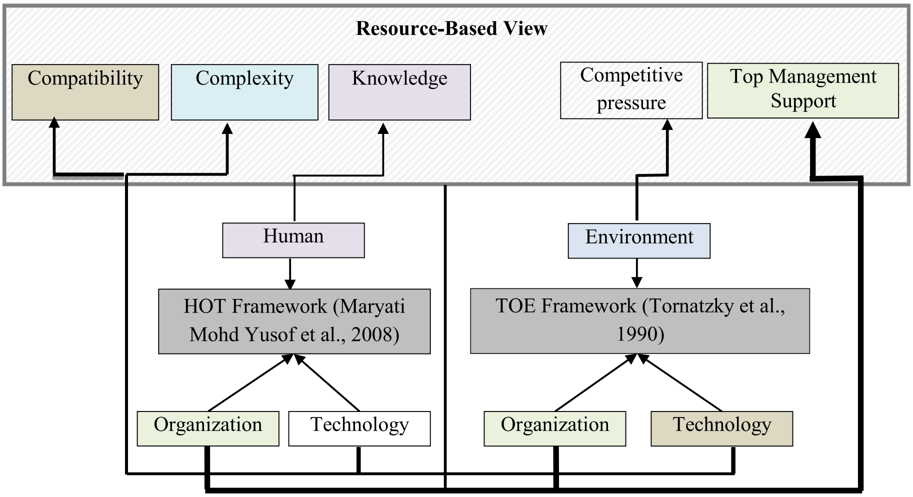


**Fig. 1** Dimensional context of BDPA adoption

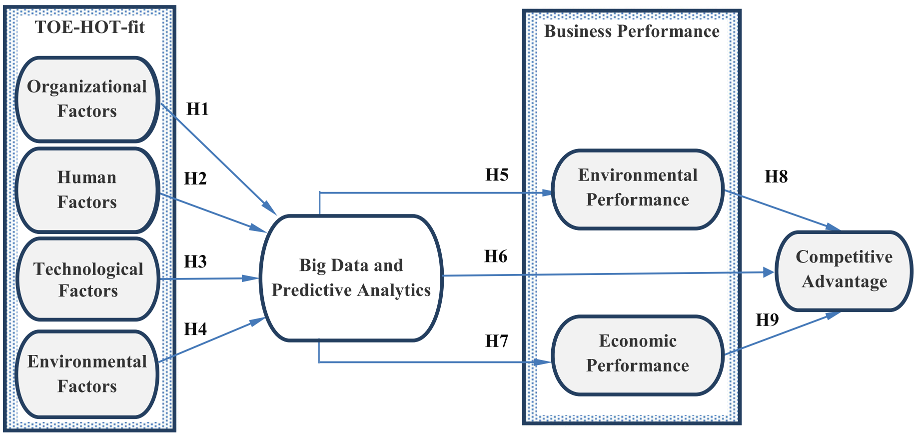


**Fig. 2** Proposed model

et al., 2017; Upadhyaya & Ahuja, 2017). Top management support is identified as "the level to which top management comprehends the value of technology and its expected benefits to the organization" (Lin, 2011). In addition, the support of management is assumed to be an imperative part of the utilization of services or innovations because it guides the required resource assignment, integration of service, and the redesigning of followed procedures (Harfoushi et al., 2016). Moreover, top management stakeholders who perceive the advantages of the new service are more likely to provide essential resources for its utilization. Furthermore, top management support is essential for promoting and furnishing the assets necessary for innovation (Oliveira et al., 2014; Talapatra et al., 2019). The level of support provided by management is essential for organizations to build an ambitious environment and provide the required assets in terms of infrastructure and technological expertise. Organizations can survive and face any internal restraints and change resistance with management's support, which eases the facilitation of new technologies. Thus, we propose the following hypothesis:

**H1** Organizational factor has a positively significant relationship with BDPA adoption

In the human fold, the knowledge level of BDPA among decision-makers and employees has an undeniable influence on its adoption. The level of knowledge of innovation helps managers follow the right procedures in the adoption and utilization of such innovations (Fahmideh & Beydoun, 2018; Kourtesis et al., 2014; Zimmermann et al., 2015). The lack of expertise and experience is regarded as a vital barrier to the adoption of technology by organizations. BDPA requires complex applications that may be perceived as complex by managers and employees with limited knowledge or experience. Hence, employees should be provided with appropriate training and courses to address their concerns, allow them to face uncertainties, and enable them to comprehend their potential benefits better. Hence, we propose the following hypothesis:

**H2** Human factor has a positively significant relationship with BDPA adoption.

In the technology dimension, the complexity and compatibility of BDPA are considered important for its adoption. The lack of sufficient knowledge might lead organizations, represented by their management, to hesitate in adopting new technology if they perceive technology as complex (Klug & Bai, 2015; Talapatra & Uddin, 2019). New technology must be manageable, easy to use, and easy to learn to enhance its utilization. Moreover, the compatibility of innovation is important for organizations to adopt it. Organizations need to ensure that the innovation contemplates their current applied systems and run smoothly with their values (Gutierrez et al., 2015; Harfoushi et al., 2016). Hence, we hypothesize the following:

**H3** Technological factor has a positively significant relationship with BDPA adoption.

In the environment dimension, we consider competitive pressure, which is defined as the pressure imposed by competitors in the business or market, as a vital factor in the adoption process (Oliveira & Martins, 2011). Competitive pressure strongly influences organizations to utilize innovative ideas to compete in the market (Nyeko & Ogenmungu, 2017). By utilizing BDPA, organizations can gain advantages over their competitors through a better understanding of business visibility. As an emerging technology, BDPA can help organizations meet their goals, particularly those that fall under higher levels of competitive pressure (Rohani, 2015). This pressure forces organizations to utilize advanced techniques to foster their development and improve their operational productivity (Alkhater et al., 2014). The impact of this factor is supported by robust evidence in the literature (Gangwar et al., 2015). Therefore, we propose the following hypothesis:

**H4** Environmental factor has a positively significant relationship with BDPA adoption.

The huge volume and nature of data growth demands skillful analysis to achieve sustainable growth. As this research focuses on BDPA in the food waste and recycling industry, it is vital to consider how BDPA adoption influences the environmental performance of enterprises. In the research model, we hypothesize that BDPA has a considerable effect on environmental performance. In general, the correlation between BDPA and enterprise performance is empirically confirmed in previous studies (Gupta et al., 2020; Wamba et al., 2020). Moreover, the literature provides evidence of the role of BDPA in environmental sustainability (Belhadi et al., 2020; Bradlow et al., 2017; Sarker et al., 2020). BDPA is seen as an emerging tactical management trend in which organizations gradually try to obtain the desired benefits from the available data to refine their green practices. Accordingly, we propose the following hypothesis:

**H5** BDPA adoption has a positively significant relationship with environmental performance.

Data-driven policies are more likely to be intellectual and help organizations achieve success (Gupta et al., 2020). By utilizing BDPA, organizations gain competitive benefits by improving their productivity and performance. Based on this, BDPA is considered an influential factor for enterprises to gain competitive advantage in the market (Behl et al., 2022; Horng et al., 2022; Shah, 2022). This relationship is previously supported in other contexts, as technologies are deemed to provoke benefits to organizations in terms of competitive advantage (Groen et al., 2013). Inspired by the RBV, incorporating emerging technologies within organizations accelerates the speed to reach competitive advantage and allows them to address uncertainties in the market (Mao et al., 2016). The competitive advantage of organizations depends on their unique deployment of operations and coordination policies endorsed by certain innovative assets to achieve its goals (Ali et al., 2021). Hence, we propose the following hypothesis:

**H6** BDPA adoption has a positively significant relationship with competitive advantage.

Organizations can occupy a large share of the market if they have notable profits through their sales, economic savings, and enhanced operations. Researchers link financial organizational performance, which is considered the most important goal of organizations, with the performance of deployed information systems (Gupta et al., 2020). By advancing their capabilities, organizations can maintain economic gains and meet stakeholders' requirements. With regards to the inner structure of organizations, organizations need to embrace prominent technological applications and concur them with an appropriate learning atmosphere to obtain the anticipated financial benefits. Incorporating individual skills within organizations can revamp resources into added value, and accordingly, lead to organizations' success. Recent literature endorses the influence of BDPA adoption on supreme financial organizational performance (Gupta et al., 2020). Building on this, utilizing non-substitutable, rare, inimitable, and valuable information with appropriate analytics techniques has a considerable impact on the competitive advantage of organizations over its contemporary competitors (Chatterjee et al., 2021). Thus, we propose the following hypothesis:

**H7** BDPA adoption has a positively significant relationship with economic performance.

As organizational operations are usually linked to ecological effects, increasing pressure is imposed by the United Nations to minimize these effects (Singh et al., 2019). Accordingly, organizations must move beyond securing economic sustainability alone to perceive eco-friendly management as an essential indicator of their performance (Yawar & Seuring, 2017). Based on this, top management should be dedicated to environmental morals by formulating appropriate strategies and deploying day-to-day management policies to reduce the environmental effects of the industry (Singh & El-Kassar, 2019). However, the evaluation of net outcomes in organizations is reflected by their performance, which can be reflected in several dimensions. Net outcomes mainly entail the economic dimension, which is represented by financial gains, investment returns, marketing aspects, sales growth, and market share (Chatterjee et al., 2021). The assessment of an organization's performance considers the level to which the organization meets its targeted aims (Keramati et al., 2010). Competitive advantage is usually linked to value-added creation and economic performance (Cantele

& Zardini, 2018). However, recent studies indicate that this can be achieved using different implementation strategies. For example, environmental management operations can present a desirable shift that allow organizations to gain a competitive advantage (Chang, 2011). Accordingly, we propose the following hypotheses:

**H8** Environmental performance has a positively significant relationship with competitive advantage.

**H9** Economic performance has a positively significant relationship with competitive advantage.

## 4 Research design

In this study, we deploy a single-stage procedure to gather, analyze, and interpret the data using the partial least squares structural equation modeling (PLS-SEM) technique. Figure 3 illustrates this procedure. After a comprehensive literature review of related studies, research hypotheses are developed to construct a new research model. A survey is then constructed by referring to previous literature and theoretical grounds. Next, a large sample of respondents is targeted for data collection, and the research model is confirmed using the PLS-SEM. The final stage of this study includes discussing the results and providing the conclusion of the study.

### 4.1 Overview of the empirical study

PLS-SEM s widely used to appraise complex cause-effect paths with latent factors (Bawack et al., 2023; Hair et al., 2014; Kock & Hadaya, 2018; Leong et al., 2023; Nguyen et al., 2022; Theadora et al., 2022). Since the 1980s, SEM has been adopted in marketing literature

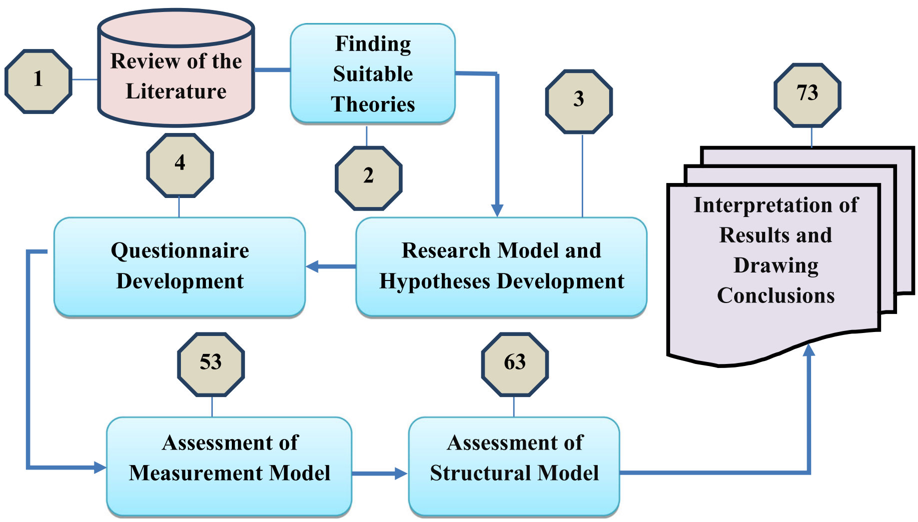


**Fig. 3** Research method

(Bagozzi, 1994) and in almost all areas of research (Hair et al., 2011). Driven by the need to examine concepts and theories, the use of SEM is embraced in the academic and marketing sectors (Steenkamp & Baumgartner, 2000). Although many researchers consider that performing covariance based structural equation modeling (CB-SEM) analysis using various tools, such as Mplus, LISREL, EQS, and Amos, is similar to SEM analysis, SEM provides a unique feature by utilizing PLS-SEM. Unlike CB-SEM, PLS-SEM investigates the variance of the dependent factors. PLS-SEM usually entails developing a research model based on a theoretical ground and evaluating it after a data collection procedure (Bullock et al., 1994). PLS-SEM also places fewer restrictions on non-normal distributions and sample sizes. Since Mardia's multivariate skewness ($\beta = 8.997$) and kurtosis ($\beta = 90.546$) have *p*-value less than 0.001, the data is non-normal and thus warrants the usage of PLS-SEM as opposed to CB-SEM. The amount of collected data depends on the number of research factors in the research model and its complexity. Two types of analysis are required to ensure the fit of the research model: measurement and structural models (Nilashi et al., 2022). While the measurement model focuses on indicator reliability, internal consistency, discriminant validity, and convergent validity, the structural model focuses on $R^2$, $f^2$, and $Q^2$ tests and hypotheses evaluation.

### 4.2 Methodology

In this study, participants are invited through formal email and social media platforms starting January 20, 2022. We target respondents from universities and industries in the Eastern Province of Saudi Arabia and obtain 130 valid responses after removing partial responses. The usable sample size exceeds the minimum sample size of 103, computed using G*power with a power level of 0.80, seven predictors, an alpha value of 0.05, and an effect size of 0.15. The responses of the participants who have previous knowledge of the concept of "Big Data and Predictive Analytics" are only considered. Demographic data including sex, age, education, and job title are collected at the beginning of the survey. Other related data including experience with industry and industrial research are collected. Figure 4 presents the procedure followed in the PLS-SEM.

We inspect four dimensions as drivers of BDPA adoption: organizational, human, technological, and environmental factors. Organizational factor is represented by top management support, Human factor is represented by the knowledge of employees, technological factor is represented by the complexity and compatibility of BDPA, and environmental factor is represented by competitive pressure. Each factor is assessed using three indicators, except technological factor which is assessed using five indicators. Organizational factor is operationalized by referring to Štemberger et al. (2011). Human factor is evaluated by referring to Akter et al. (2016). Human factor is reflected in having adequate experience or development capacity in terms of technology (Sulaiman, 2011). For the technological factor, we refer to the measures of Nyeko and Ogenmungu (2017) to assess compatibility and complexity. Environmental factor is assessed by referring to Akça and Özer (2016). BDPA adoption also has three indicators, which are taken from Akter et al. (2016). For the economic and environmental performance, each indicator is evaluated using three indicators from Akter et al. (2016) and Khattak et al. (2021), respectively. Finally, competitive advantage is assessed using three items adopted from Sołoducho-Pelc and Sulich (2020). Although we refer to these studies for the adoption of the indicators, we adjust them to match the context of the study (Thompson & Sinha, 2008). We also refer to experts' assessments of the survey and adjust the items based on their opinions. Before distributing the survey, we assess the content validity of the

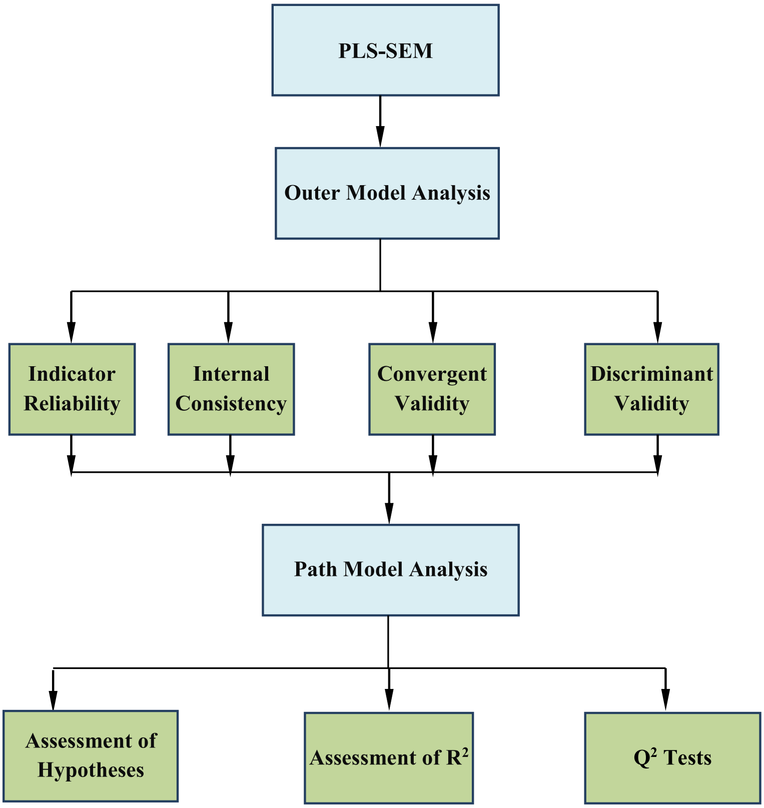


**Fig. 4** PLS-SEM procedure (Hair et al., 2013)

survey constructs and indicators with the aid of three experts in the information system field to ensure that these indicators actually measure the constructs they represent. Subsequently, the comments of experts are addressed.

### 4.3 Data collection

Table 1 shows that 60% of the respondents are male. Most participants are in the age range of 35–44 years (26.2%) and 45–54 years (33.1%). Approximately 41.5% of the respondents have a Ph.D., and 51.5% of the respondents are consultants. Lastly, 55.4% of the respondents are familiar with BDPA.

### 4.4 Non-response bias

Since this study adopts a cross-sectional approach, common method bias (CMB) could be a potential issue. Thus, procedural and statistical remedies are applied. Confidentiality and anonymity of answers are guaranteed for procedural remedies (Tan & Ooi, 2018). In terms

**Table 1** Demographic results of the participants (N = 130)

| Feature | Item | Frequency | Percentage (%) |
|---|---|---|---|
| Gender | Female | 52 | 40.0 |
| | Male | 78 | 60.0 |
| Age | Under 25 | 8 | 6.2 |
| | 25–34 | 21 | 16.2 |
| | 35–44 | 34 | 26.2 |
| | 45–54 | 43 | 33.1 |
| | 55–64 | 24 | 18.5 |
| Work experience with the industry | Less than 3 years | 35 | 26.9 |
| | 3–5 years | 29 | 22.3 |
| | 6–8 years | 28 | 21.5 |
| | More than 8 years | 38 | 29.2 |
| Level of education | Senior high school or below | 31 | 23.8 |
| | Bachelor | 10 | 7.7 |
| | Master | 35 | 26.9 |
| | Ph.D | 54 | 41.5 |
| Job title | Chief executive officer | 11 | 8.5 |
| | Director of organization | 8 | 6.2 |
| | IT manager | 10 | 7.7 |
| | Mid-level manager | 22 | 16.9 |
| | Senior manager | 12 | 9.2 |
| | Consultant | 67 | 51.5 |
| Level of familiarity with big data and predictive analytics | High familiarity | 72 | 55.4 |
| | Moderate familiarity | 46 | 35.4 |
| | Low familiarity | 12 | 9.2 |

of statistical remedies, this study adopts the approach of Liang et al. (2007). Since all substantive factor loadings (Ra) are significant and most of the method factor loadings (Rb) are insignificant, CMB is not a major concern in this study (see Table 2).

## 5 Data analyses and results

### 5.1 Assessment of the outer measurement model

The survey questions (see Table 8 in Appendix A) are examined for reliability and validity based on three main assessments: (1) convergent validity, (2) internal consistency, and (3) discriminant validity (Tew et al., 2022; Theadora et al., 2022). The first test is proven through the values of the outer loading that surpass 0.7 (Hair et al., 2013) apart from HF1, BDPA2, and OF3. Because all AVE values are above 0.5 (Lim et al., 2022), HF1, BDPA2, and OF3 are retained. The values for all outer loadings are significant at $p < 0.001$. Internal consistency is supported by Dijkstra-Henseler's rho (rhoA) and composite reliability (CR) values above

**Table 2** Common method bias

| Latent construct | Indicators | Substantive factor loading (Ra) | $Ra^2$ | Method factor loading (Rb) | $Rb^2$ |
|---|---|---|---|---|---|
| BDPA | BDPA—> BDPA1 | $0.679^{***}$ | 0.461 | $0.106^{NS}$ | 0.011 |
| | BDPA—> BDPA2 | $0.798^{***}$ | 0.637 | $-0.099^{NS}$ | 0.010 |
| | BDPA—> BDPA3 | $0.873^{***}$ | 0.762 | $-0.013^{NS}$ | 0.000 |
| COMA | COMA—> COMA1 | $0.847^{***}$ | 0.717 | $0.062^{NS}$ | 0.004 |
| | COMA—> COMA2 | $0.879^{***}$ | 0.773 | $0.035^{NS}$ | 0.001 |
| | COMA—> COMA3 | $0.941^{***}$ | 0.885 | $-0.104^{NS}$ | 0.011 |
| ECP | ECP—> ECP1 | $1.029^{***}$ | 1.059 | $-0.166^{*}$ | 0.028 |
| | ECP—> ECP2 | $0.840^{***}$ | 0.706 | $0.044^{NS}$ | 0.002 |
| | ECP—> ECP3 | $0.788^{***}$ | 0.621 | $0.118^{NS}$ | 0.014 |
| EF | EF—> EF1 | $0.760^{***}$ | 0.578 | $0.018^{NS}$ | 0.000 |
| | EF—> EF2 | $0.836^{***}$ | 0.699 | $-0.043^{NS}$ | 0.002 |
| | EF—> EF3 | $0.775^{***}$ | 0.601 | $0.026^{NS}$ | 0.001 |
| ENVP | ENVP—> ENVP1 | $0.849^{***}$ | 0.721 | $0.046^{NS}$ | 0.002 |
| | ENVP—> ENVP2 | $0.948^{***}$ | 0.899 | $-0.066^{NS}$ | 0.004 |
| | ENVP—> ENVP3 | $0.863^{***}$ | 0.745 | $0.019^{NS}$ | 0.000 |
| HF | HF—> HF1 | $0.766^{***}$ | 0.587 | $-0.170^{NS}$ | 0.029 |
| | HF—> HF2 | $0.785^{***}$ | 0.616 | $0.091^{NS}$ | 0.008 |
| | HF—> HF3 | $0.833^{***}$ | 0.694 | $0.041^{NS}$ | 0.002 |
| OF | OF—> OF1 | $0.798^{***}$ | 0.637 | $0.070^{NS}$ | 0.005 |
| | OF—> OF2 | $0.766^{***}$ | 0.587 | $0.121^{NS}$ | 0.015 |
| | OF—> OF3 | $0.867^{***}$ | 0.752 | $-0.264^{NS}$ | 0.070 |
| TF | TF—> TF1 | $0.550^{***}$ | 0.303 | $0.220^{NS}$ | 0.048 |
| | TF—> TF2 | $0.558^{***}$ | 0.311 | $0.252^{*}$ | 0.064 |
| | TF—> TF3 | $0.828^{***}$ | 0.686 | $0.027^{NS}$ | 0.001 |
| | TF—> TF4 | $1.034^{***}$ | 1.069 | $-0.317^{*}$ | 0.100 |
| | TF—> TF5 | $0.938^{***}$ | 0.880 | $-0.180^{NS}$ | 0.032 |
| Average | | 0.824 | 0.692 | $-0.005$ | 0.018 |

0.7 (Balachandran et al., 2022). Discriminant validity is supported by the Fornell-Larcker and cross-loadings tests. Tables 3 and 4 present the results.

### 5.2 Assessment of the inner structural model

The analysis of the inner model is applied broadly in social sciences (Hair et al., 2011). The bootstrapping technique is used to assess the inner structural model. The variance inflation factor values are between 1.000 and 2.047 and are below the value of 3, indicating the absence of multicollinearity (Lo et al., 2022).

Table 5 and Fig. 5 show the results. The results indicate that all paths are significant, except for H1 and H3. The confidence interval has a value of zero, which affirms that neither hypothesis is supported. The variance explained ($R^2$) values for the inner model, which

**Table 3** Reliability and validity

| Constructs | Items | Loadings (*p*-levels) | rhoA (ρA) | CR | AVE |
|---|---|---|---|---|---|
| BDPA | BDPA1 | 0.785 | 0.709 | 0.824 | 0.610 |
| | BDPA2 | 0.692 | | | |
| | BDPA3 | 0.858 | | | |
| COMA | COMA1 | 0.902 | 0.869 | 0.917 | 0.786 |
| | COMA2 | 0.911 | | | |
| | COMA3 | 0.846 | | | |
| ECP | ECP1 | 0.876 | 0.870 | 0.915 | 0.782 |
| | ECP2 | 0.885 | | | |
| | ECP3 | 0.892 | | | |
| EF | EF1 | 0.888 | 0.852 | 0.817 | 0.601 |
| | EF2 | 0.708 | | | |
| | EF3 | 0.717 | | | |
| ENVP | ENVP1 | 0.894 | 0.865 | 0.917 | 0.786 |
| | ENVP2 | 0.888 | | | |
| | ENVP3 | 0.879 | | | |
| HF | HF1 | 0.596 | 0.867 | 0.823 | 0.615 |
| | HF2 | 0.908 | | | |
| | HF3 | 0.816 | | | |
| OF | OF1 | 0.847 | 0.726 | 0.836 | 0.634 |
| | OF2 | 0.873 | | | |
| | OF3 | 0.650 | | | |
| TF | TF1 | 0.811 | 0.877 | 0.884 | 0.604 |
| | TF2 | 0.788 | | | |
| | TF3 | 0.857 | | | |
| | TF4 | 0.701 | | | |
| | TF5 | 0.721 | | | |

BDPA = big data and predictive analytics, COMA = competitive advantage, ECP = economic performance, EF = environmental factors, ENVP = environmental performance, HF = human factors, OF = organizational factors, TF = technological factors

**Table 4** Fornell-Larcker criterion

| | BDPA | COMA | ECP | EF | ENVP | HF | OF | TF |
|---|---|---|---|---|---|---|---|---|
| BDPA | *0.781* | | | | | | | |
| COMA | 0.443 | *0.887* | | | | | | |
| ECP | 0.277 | 0.612 | *0.884* | | | | | |
| EF | 0.404 | 0.342 | 0.227 | *0.775* | | | | |
| ENVP | 0.425 | 0.798 | 0.640 | 0.264 | *0.887* | | | |
| HF | 0.454 | 0.392 | 0.350 | 0.343 | 0.453 | *0.784* | | |
| OF | 0.441 | 0.824 | 0.677 | 0.331 | 0.889 | 0.498 | *0.796* | |
| TF | 0.362 | 0.626 | 0.841 | 0.222 | 0.645 | 0.423 | 0.661 | *0.777* |

The italic values in the main diagonal are the square roots of AVEs

**Table 5** Path coefficient result ($N = 130$)

| Hypotheses | PLS path | Original sample (O) | Sample mean (M) | Standard deviation (STDEV) | T Statistics (\|O/STDEV\|) | $p$ values | Bias corrected confidence interval | |
|---|---|---|---|---|---|---|---|---|
| H6 | BDPA—> COMA* | 0.126 | 0.127 | 0.057 | 2.220 | 0.026 | 0.019 | 0.242 |
| H7 | BDPA—> ECP** | 0.277 | 0.285 | 0.099 | 2.795 | 0.005 | 0.071 | 0.455 |
| H5 | BDPA—> ENVP*** | 0.425 | 0.433 | 0.076 | 5.608 | 0.000 | 0.252 | 0.553 |
| H9 | ECP—> COMA* | 0.170 | 0.174 | 0.072 | 2.372 | 0.018 | 0.033 | 0.319 |
| H4 | EF—> BDPA** | 0.240 | 0.244 | 0.077 | 3.100 | 0.002 | 0.074 | 0.382 |
| H8 | ENVP—> COMA*** | 0.636 | 0.631 | 0.074 | 8.630 | 0.000 | 0.484 | 0.767 |
| H2 | HF—> BDPA* | 0.244 | 0.245 | 0.105 | 2.324 | 0.020 | 0.039 | 0.448 |
| H1 | OF—> BDPA^NS | 0.186 | 0.197 | 0.135 | 1.377 | 0.168 | – 0.097 | 0.432 |
| H3 | TF—> BDPA^NS | 0.082 | 0.091 | 0.116 | 0.708 | 0.479 | – 0.138 | 0.313 |

* Significant at $p < 0.05$ level
** Significant at $p < 0.01$ level
*** Significant at $p < 0.001$ level
NS Not supported

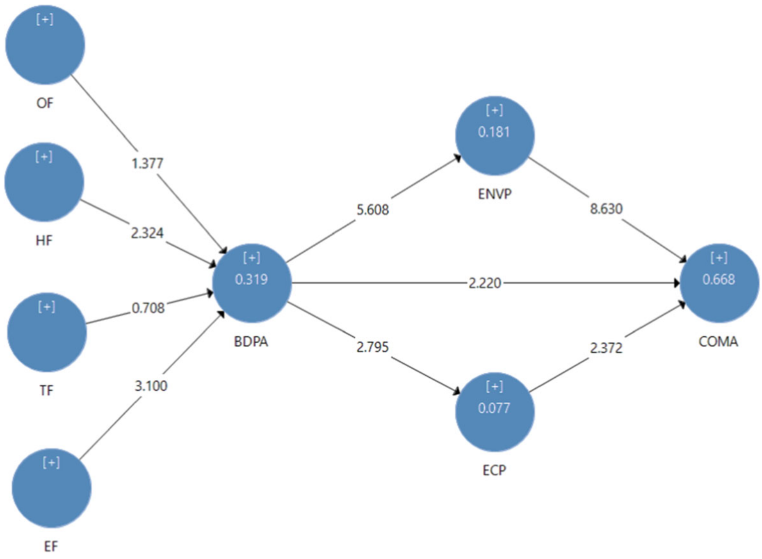


**Fig. 5** Results of the structural model analysis

indicate the variations in BDPA, COMA, ECP, and ENVP, are 0.319, 0.668, 0.077, and 0.181, respectively. The results indicate substantial, substantial, weak, and moderate predictive accuracies for BDPA, COMA, ECP, and ENVP, respectively (Cohen, 1988). All effect size (f2) values range from 0.005 to 0.637, suggesting that the study has a small-to-large effect. Finally, the $Q^2$ test is used to assess the predictive relevance of the dependent factors. The result of this test, which is performed using the blindfolding method, should be greater than zero (Wan et al., 2022; Yuan et al., 2022). The results of the $Q^2$ test for BDPA, COMA, ECP, and ENVP are 0.164, 0.513, 0.053, and 0.137, respectively, meeting the predictive relevance condition of the research model.

## 6 Discussion

Research outcomes support the acceptance of most research paths and are interpreted in this section. First, according to the findings, knowledge and competitive pressure are essential drivers for evaluating BDPA adoption by waste and recycling organizations. However, H1 and H3 are rejected, as the *p*-value for each hypothesis should be less than 0.05 to have a significant impact (Hair et al., 2013). Top management support has an insignificant influence on the stakeholders involved in BDPA adoption. This result is in line with those of previous studies in other contexts (Alharbi et al., 2016; Tashkandi & Al-Jabri, 2015). The insignificant relationship between the support provided by management and BDPA adoption can be justified by the lack of strategic planning at the organizational level to support the adoption process. Top management might not pay attention to conceptualizing the accurate requirements of the innovation and might lack strategic coordination between decision-makers and employees to reach accurate decisions in this context. As an innovation, business and IT managers may not be fully aware of the prospective gains of BDPA that surpass its deployment-related risks (Harfoushi et al., 2016). The results indicate that top management has a neutral position on

BDPA adoption. This also reflects the immaturity of BDPA in Saudi Arabia and indicates that managers might have concerns about the hidden costs of BDPA adoption.

Second, staff knowledge has an influential impact on BDPA adoption. Human resources perform a significant task in designing and accepting new strategies to improve the performance of any organization (Sulaiman, 2011). An institution that successfully accepts new technologies and services depends strongly on staff experience and developmental capacity (Angela Lin & Chen, 2012). When institutions have professional staff with experience and knowledge, using new technologies is easy (Rohani, 2015). Moreover, organizations, whose staff has more information and experience, offer less resistance to technology usage (Rohani, 2015; Emma King & Boyatt, 2015). The absence of in-house knowledge is considered the most significant barrier to understanding technology utilization. In any institution, insufficient knowledge and IT skills impose considerable difficulty on IT acceptance and present a deficiency in the organization's performance (Yeboah-Boateng & Essandoh, 2014). The literature stresses the importance of a deep understanding of BD concepts for operations management (Addo-Tenkorang & Helo, 2016). The significance of consistency among employees in terms of their understanding of the main concepts and terminologies of BDPA is essential for promoting efficiency and gaining competitive advantage within the market. The significant impact between knowledge and BDPA adoption provides ample insights into operations management within organizations, as it indicates the importance of employees' knowledge to facilitate all the expected benefits from BDPA adoption. The expected benefits include evaluating supply chain risks, measuring performance, and predicting revenue.

Third, there is an insignificant correlation between compatibility and BDPA adoption. This result contradicts the findings presented by the literature in other research contexts (Lian et al., 2014; Nyeko & Ogenmungu, 2017). Otherwise, incompatibility with BDPA might not be perceived as a restriction to an organization's access to its potential benefits. As compatibility with an organization's groundwork requires addressing the consistency and incorporation problems of BDPA (Başaran & Hama, 2018), employees are seemingly keen to make the required changes to adapt to BDPA. This allows the smooth achievement of business processes and successful enforcement of the service (Ramsey et al., 2016). This study also considers complexity. Although less complexity in incorporating BDPA with existing processes and extant tools is advantageous, this advantage is not significant in this research. This finding contradicts that of Chiu et al. (2017), who indicate that reducing complexity in terms of facilitating the deployment of existing techniques and schemes helps in implementing the service effectively. It seems that complexity and lack of compatibility are insignificant barriers to BDPA adoption. The anticipated gains of BDPA adoption, which is expected to overcome other complexities in performing tasks, can justify this result (Dubey et al., 2019). The level of complexity does not lead to a more desirable perception of BDPA in this research, since BDPA adoption requires special skills and a comprehensive understanding to utilize its services. The results show that managers in organizations perceive staff knowledge as more important than compatibility and less complexity of BDPA. Therefore, vendors of BDPA tools should present all-inclusive and pre-selling benefits, such as appropriate promotion of the service, required coaching, consultative services, and post-sale services, to link the provided service to the organization's requirements and bridge the knowledge gap. Competitive pressure has a significant effect on BDPA adoption. This effect is recognized in the literature, considering innovation adoption settings (Harfoushi et al., 2016; Yones and Fares, 2017). In other words, BDPA adoption occurs when organizations find that such adoption preserves their competitive position and enhances their competitive advantage (Yones and Fares, 2017). Moreover, as organizations face strong competition, they have a propensity to deploy amendments more strongly and respond more swiftly (Harfoushi et al., 2016). As competitors deploy a new service, other enterprises encounter powerful competition and thus sense more strain to utilize this innovation (Nyeko & Ogenmungu, 2017).

H8 and H9 are endorsed by the statistical results that support research outcomes in other contexts. For example, the path between environmental performance and competitive advantage is affirmed by Norcia et al. (1993), while the path between economic performance and competitive advantage is endorsed by Chatterjee et al. (2021). Referring to RBV theory, this research considers BDPA as an important resource for organizations. Operations managers can utilize organizational resources in terms of BDPA to enhance the sustainable productivity of organizations and, by extension, preserve their position in the market. It is important to balance the effective usage of BDPA as an important asset in the organization, focusing on the determinants of its adoption to meet the effectual operational management process and, accordingly, the overall success of the organization.

This study resembles that of Maroufkhani et al. (2020), who examine the impact of BDPA adoption on small to medium-sized organizations. However, in the abovementioned reference, the research model investigates the impact of BDPA adoption on financial and market performance. Our research model explores the competitive advantage, economic performance, and environmental performance of organizations through the lens of BDPA adoption. In the context of this study, our research focuses on environmental performance, as we consider the impact of BDPA on the food recycling industry, which is rarely discussed in the literature.

### 6.1 Theoretical contributions

When deploying the theory in new contexts, the theoretical contributions can be emphasized by the theoretical feedback loop. This indicates that researchers need to understand new aspects of the theory in a newly adopted context (Whetten, 1989). The adoption of theories in a new context stresses that previous metaphors must be modified to challenge existing rationales while endorsing accepted theories. This sheds in-depth focus on the accepted views of the conceptualization of theories while exploring human capabilities, contextual aspects, and organizational resources. Hence, in this study, the research contributions are reflected in terms of added value to the adopted theories and previous literature while catching a glimpse of the food waste and recycling industry.

First, the RBV theory is adopted in this study to investigate the impact of managers' utilization of resources on meeting sustainable goals. This study suggests unconventional theoretical lenses for investigating the impact of BDPA adoption on business performance. Instead of formulating business sustainability based on a group of practices, RBV theory is deployed to formulate business sustainability based on a set of capabilities (Yuen et al., 2019). Building on the RBV perspective, if operated tactically, BDPA can provide a sustained competitive advantage in the food waste and recycling industry. This perception supplements contemporaneous theoretical literature anchored in manager and organizational research. The resources in the RBV theory are usually focused on the internal structure of organizations, with less emphasis on contextual aspects, as it adopts an inside-outside view. Our research overcomes this limitation by exploring the external environment and adopting the competitive advantage factor along with the internal factors of the organization. The essence of this contextually confirms the significance of reaching a fit between organizational resources, BDPA capabilities, and the external environment.

Second, this research can refine current knowledge by elaborating on the impact of BDPA adoption on sustainable performance through the theoretical lens of contingency RBV theory. This study adds theoretical insights into dynamic RBV by defining and investigating two forms of business performance: economic and environmental performance. The impacts of environmental and economic performance on the competitive advantage of an organization within the food waste and recycling industry are investigated through the lens of the RBV theory.

Third, the research builds on theoretical grounds and adds to existing knowledge by researching the effects of the four dimensions on BDPA adoption in food waste enterprises. These dimensions are explored in the previous literature on several disciplines by incorporating different factors into each dimension (Erlirianto et al., 2015). Using the TOE and HOT-fit frameworks, this study evaluates how technological, organizational, environmental, and human factors influence business performance through the intermediation of BDPA adoption. This study sheds light on the imperative role of BDPA as an intermediate variable in the relationship between several dimensions (human, organizational, environmental, and technological) and the performance and competitive advantage of an organization.

Fourth, referring to the adopted theories, the research model adds to the existing theories of RBV, TOE, and HOT-fit by examining the impact of BDPA on an organization's performance and boosts the small but increasing body of literature allocated to investigating this issue in the industry context. In addition, the research explores BDPA adoption in a rarely touched context, which is the food recycling and waste industry. Although the topic of this study is gaining increasing interest, it is investigated through a holistic lens (Wamba et al., 2020), with little focus on providing empirical support for the proposed approaches. We argue that in the context of the food waste and recycling industry, utilizing BDPA in organizations allows them to lead the market and address the increasing challenges they face.

Fifth, the research addresses the space between the theoretical basis and practical applications through the evaluation of several factors proposed based on robust theories from the views of experts, scholars, and decision-makers in academic and industrial fields. From a methodological perspective, the findings reveal that BDPA adoption in food waste and recycling organizations has several crucial determinants based on the PLS-SEM approach. The inclusion of technological, organizational, environmental, and human factors provides insights into how BDPA impacts business sustainability. The outcomes suggest that organizations can address their strategic targets through the intercession of economic and environmental performance, leading to long-term competitive advantage.

Sixth, research on BDPA has gained increasing attention in the context of operational management within organizations. Data analytics approaches are considered important assets for the operational management of organizations (Mishra et al., 2018a). According to Bi and Cochran (2014), BDPA significantly influences IS performance of information systems in industries. BDPA adoption in an organization's operations can help reduce operational costs and improve revenues by deploying novel resources, addressing potential risks, and gaining a full understanding of customers (Sanders & Ganeshan, 2015). However, research in this context is subject to several obstacles in terms of determining factors and the quality of outcomes. For example, a shortage of data quality in supply chain management raises the need to adopt perfect BDPA approaches in organizations (Hazen et al., 2014). Hence, it is important to gain an in-depth understanding of the role of BDPA in enhancing operational management (Bhatti et al., 2022). This can be achieved by adopting a knowledge-based view to explore the factors that influence BDPA adoption, and how the adoption process impacts the competitive advantage of organizations. Although the importance of BDPA in organizational performance and decision-making processes is endorsed in previous literature (Fosso Wamba et al., 2018), the commercial value of BDPA in organizations' operational process is not fully explored (Ji et al., 2022). The research findings not only support previous literature on the importance of BDPA in the organization's performance but also amplify the understanding of the deployment of the RBV theory, focusing on the capabilities of BDPA. This finding embellishes the literature on data-driven capabilities by integrating the roles of competitive pressure and knowledge in BDPA adoption and their impact on organizational performance. This research sheds light on how BD resources help organizations develop competency in the market. It also concentrates on the impact of integrating several factors on BD analytics capabilities (Mikalef et al., 2019b).

Finally, the research model is examined in a developing environment with an eagerness to achieve a competitive advantage on a global level. Saudi Arabia has introduced the Vision 2030 framework, which aims to achieve digital transformation of the main sectors within the kingdom (Alshahrani et al., 2022). The proposed vision integrates the broad assets of the BDPA infrastructure into the plans of governmental and private organizations to meet its goals. Considering the digital shift, Saudi Arabia is recognized by the European Center of Digital Competitiveness as a paramount country (Alshahrani et al., 2022). For example, the Saudi Data and Artificial Intelligence Authority aims to achieve artificial intelligent digitization. Hence, exploring BDPA adoption in this environment provides important insights into the impact of different factors on the operational management of organizations.

### 6.2 Implications for practice

Food waste issues in developing nations are considered a significant threat to sustainable development and food waste management systems (Thi et al., 2015). According to Dung et al. (2014), food waste in developing and developed countries is 56 kg/year and 107 kg/year, respectively. Based on UN estimations, approximately one-third of the food in the world is wasted, leading to an estimated loss of US$1 trillion annually (Jenkins et al., 2022). In the supply chain, food loss can occur at any stage of manufacturing, retail, export, distribution, or consumption (Surucu-Balci & Tuna, 2021). Following the retail process, food can be wasted in markets, restaurants, hotels, or houses (Parfitt et al., 2010). Food waste has devastating effects on climate change as it increases greenhouse gas emissions (Adhikari et al., 2006). An essential outcome of this study is the vital role of the interventions carried out by organizations to improve their performance and gain added value among their competitors in the market to address increasing threats to the environment. As the issue of food waste is highly indispensable in organizations' agendas, organizations in the food waste and recycling industry should follow advanced techniques to investigate, collect required data, analyze, visualize, and support decision-makers with practical directions.

First, by shedding light on an important managerial implication, this study stresses the influential role of BDPA on the success of eco-friendly businesses. BDPA adoption within the food waste and recycling industry, as perceived by managers, is anticipated to preserve the organization's position in the industry and allow it to gain a competitive advantage. Thus, research outcomes can be exerted in other domains, as the deployment of BDPA can bring benefits to organizations, encourage them to follow green practices, and enhance their strategies. Second, data analytics techniques have gained business enthusiasm for their anticipated benefits. However, the deployment of such innovations faces many challenges that need to be addressed (Nishant et al., 2020). Several significant barriers are justified by restructuring and implementing lags (Gupta et al., 2020). Thus, addressing this issue, by allocating complementary resources to allow efficient investment in a data analytics environment is of great importance. To adopt more sustainable choices, the management should support employees with suitable training to allow better involvement with the BDPA adoption procedure, as the knowledge and experience of the employees is a prerequisite for the adoption process. Organizations should communicate with employees, grasp the difficulties they face while using new technologies, and aid them in addressing technical problems (Wang & Qualls, 2007). The impact of the human factor, in terms of knowledge, sheds light on the importance of policies followed by organizations to ensure that they fulfill this dimension. Third, the findings reveal the impact of BDPA on the organization's gains in terms of environmental and economic performance, which can be utilized by the organization to set more oriented goals endorsed by the right training of employees and technical support and ensure appropriate utilization of the analytical culture. Organizations can allocate appropriate funds to invest in framing the data culture, which entails talented employees, capable managers, and the required resources. The performance of an organization can be enhanced if management capabilities are utilized to reach data-driven decisions, which is proven to be a winning choice in competitive markets. The results of this study show that data-driven decisions impose a higher impact if supported by technical analysis and conclusive management expertise. Finally, this study stresses the impact of environmental performance on an organization's competitive advantage. This result reflects global concerns about deploying eco-friendly practices in industries.

### 6.3 Limitations and future directions

This study has some limitations that should be addressed in future studies. First, although the design of the research model is based on experts' participation in which four dimensions are considered, the factors that represent each dimension could be extended to cover wider folds in the evaluation process such as the structure and size of the organization. Other important features of the organization can also be considered, such as risk-taking capability, culture, and economic status. As presented in Tables 6 and 7 in Appendix A, these dimensions are considered in the literature in various settings and are based on diverse representative factors to assess an enterprise's performance, net benefit, and adoption of technology. Second, the research model can be augmented to incorporate more research variables that could present practical directions for industry decision-makers. Third, the research targets decision makers in Saudi Arabia; thus, the generalizability of the findings requires careful exploration. Fourth, the research could be expanded to cover other contexts, such as agricultural waste, solid waste, or household waste. Fifth, a comparative study between adopters and non-adopters of BD technologies in food industries may better provide the perspective of decision-makers in adopting BDPA and its benefits for industry performance.

Finally, the integration of more than one methodology to present more robust outcomes is widely deployed in the literature. Previous studies use a hybrid approach that integrates both multiple-criteria decision-making (Prakash & Srivastava, 2019; Yin et al., 2022) and SEM, and machine learning (e.g., Artificial Neural Network) and SEM (Çakıt et al., 2020) to examine the research model. Future studies could integrate these hybrid approaches to model decision-making problems for BD adoption in eco-friendly businesses.

## 7 Conclusion

This study investigates the role of BDPA in improving the competitive advantage of the food industry in Saudi Arabia. Several theoretical grounds of RBV, TOE, and HOT fit are used to explore the dimensions that have an essential impact on BDPA adoption. The model examines how the successful implementation of BDPA can influence organizations' market share and performance. The links between organizational, human, environmental, and technological constructs and BDPA adoption are analyzed in this study. Furthermore, this study reveals the impact of environmental and economic performance, through BDPA adoption, on competitive advantage in the food industry. The study uses the PLS approach to support research model development and proposed hypotheses. The appraisal of the research model proves its reliability and validity, along with its anticipated predictive power. As the definition of the determinant variables of BDPA at the organizational level is supported by the research analysis, a better conceptualization of the instructional utilization of BDPA in the food waste and recycling industry can be framed. The findings highlight the significant role of incorporating BDPA by the organizations to gain a desirable share in the market and enhance their performance.

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**Data availability** The datasets generated and analyzed during the current study are not publicly available due the fact that they constitute an excerpt of research in progress but are available from the first author on reasonable request.

### Declarations

**Conflict of interest** The authors have no competing interests to declare that are relevant to the content of this article. All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.



## Appendix 1

See Tables 6, 7, 8.

**Table 6** HOT-fit model in previous literature

| References | Context | Theory | Technological factors | Human factors | Organizational factors | Environmental factors | Dependent factor |
|---|---|---|---|---|---|---|---|
| Irfan (2020) | e-learning | HOT- Fit model | Information quality<br>System quality<br>Service quality | System use<br>User satisfaction | Structure<br>Environment | NA | Net benefit |
| Maryati Mohd Yusof et al. (2008) | Health information systems | HOT- Fit model | Information quality<br>System quality<br>Service quality | System use<br>User satisfaction | Structure<br>Environment | NA | Net benefit |
| Alam et al. (2016) | Human resource information system | HOT- Fit model | IT Infrastructure<br>Perceived compatibility<br>Perceived complexity | Innovativeness of senior executives<br>IT capabilities of staff | Relative advantage<br>Top management support<br>Centralization<br>Formalization<br>Perceived cost | Competitive pressure<br>Technology vendor support<br>Government regulations and support | Adoption |
| Maryati M Yusof and Arifin (2016) | Laboratory information systems | HOT-Fit model | Information quality<br>System quality<br>Service quality | System use<br>User satisfaction | Pre-pre-analytic<br>Pre-analytic<br>Post-analytic<br>Post-post-analytic | NA | Net benefit |
| Mirabolghasemi et al. (2019) | Higher education | HOT- Fit model | Relative advantage<br>Perceived compatibility<br>Perceived complexity | Computer Self-efficacy<br>Subjective Norm | IS/IT Knowledge<br>Management Support | NA | E-learning Readiness |
| Erlirianto et al. (2015) | Electronic medical record | HOT- Fit model | Information quality<br>System quality<br>Service quality | System use<br>User satisfaction | Structure<br>Environment | NA | Net benefit |
| Agustini et al. (2020) | E-report card | HOT- Fit model | Information quality<br>System quality<br>Service quality | System use<br>User satisfaction | Structure | NA | Net benefit |
| Sibuea et al. (2017) | Hospital information system | HOT- Fit model | Information quality<br>System quality<br>Service quality | System use<br>User satisfaction | Structure<br>Environment | NA | Net benefit |

**Table 7** TOE Model in previous literature

| References | Context | Theory | Technological factors | Organizational factors | Environmental factors | Dependent factor |
|---|---|---|---|---|---|---|
| Aboelmaged (2014) | E-maintenance readiness | TOE model | Technology infrastructure<br>Technological competence | Expected e-maintenance<br>Expected e-maintenance<br>Level of firm's maintenance priority<br>Firm size | Competitive pressure | E-maintenance readiness |
| Wenjuan Xu et al. (2017) | ERP assimilation | TOE model | Relative advantage<br>Compatibility<br>Complexity | Top management support<br>Organization fit<br>Financial commitment | Competitive Pressure | ERP assimilation |
| Mohamed et al. (2009) | Web technology investment | TOE model | Technology Competence | Firm Size<br>Managerial Beliefs | Pressure Intensity | Web technology investment |
| Mujalli and Almgrashi (2020) | Audit Software Adoption | TOE model | Relative advantage<br>Compatibility<br>Complexity | Management support<br>Technological readiness<br>Training and education | Normative<br>Coercive<br>Mimetic | Adoption |
| Kandil et al. (2018) | Cloud computing | TOE model | Relative advantage<br>Compatibility<br>Complexity<br>Security and Trust | Management support<br>Technological readiness<br>Maturity and Performance Issues | Telecommunication Infrastructure<br>Internet Service Provider<br>Trading Partner support<br>Trading Partner Pressure | Cloud computing adoption |

**Table 7** (continued)

| References | Context | Theory | Technological factors | Organizational factors | Environmental factors | Dependent factor |
|---|---|---|---|---|---|---|
| Palacios-Marqués et al. (2015) | SMEs | TOE model | Technology Integration<br>IT Expertise | Commitment | Vertical competition (Suppliers)<br>Vertical competition (User) | Knowledge exchange through web apps |
| Gangwar et al. (2015) | Cloud computing adoption | TAM-TOE model | Relative advantage<br>Compatibility<br>Complexity | Organizational competency<br>Training and education<br>Top management support | Competitive pressure<br>Trading partner support | Adoption intention |

**Table 8** Survey items

| Factor | Item | Indicator | References |
|---|---|---|---|
| Organizational factor (top management support) | OF1 | Top management understands the significance of BDPA | Štemberger et al. (2011) |
| | OF2 | Top management actively deploys BDPA | |
| | OF3 | Top management supports initiatives related to BDPA | |
| Human factor (knowledge) | HF1 | Our employees have a high level of knowledge | Akter et al. (2016) |
| | HF2 | Our employees have a high level of expertise | |
| | HF3 | Our employees have a high level of technological knowledge | |
| BDPA | BDPA1 | Our enterprise intends to adopt BDPA in the future | Akter et al. (2016) |
| | BDPA2 | Our enterprise recommends BDPA to other enterprises | |
| | BDPA3 | Our enterprise follows the required strategies for the utilization of BDPA | |
| Competitive advantage | COMA1 | Our enterprise has a considerable advantage over other competitors | Sołoducho-Pelc and Sulich (2020) |
| | COMA2 | Our enterprise has new standards in the area | |
| | COMA3 | Our enterprise surpasses competitors in terms of innovation and technology | |
| Economic performance | ECP1 | Profit growth | Akter et al. (2016) |
| | ECP2 | Added value | |
| | ECP3 | Sales growth | |
| Environmental performance | ENP1 | Designing reusable products | Khattak et al. (2021) |
| | ENP2 | Regulating eco-friendly strategies | |
| | ENP3 | Eco-friendly products and services | |
| Technological factor (compatibility and complexity) | TF1 | Integrating BDPA tools in our enterprise's procedures is applicable | Nyeko and Ogenmungu (2017) |
| | TF2 | No complex skills are required for using BDPA | |
| | TF3 | Using BDPA runs with our enterprise's procedures | |

**Table 8** (continued)

| Factor | Item | Indicator | References |
|---|---|---|---|
| | TF4 | Using BDPA runs with our enterprise's current technologies | |
| | TF5 | Using BDPA runs with our enterprise's aims and goals | |
| Environmental factor (competitive pressure) | EF1 | BDPA allows our enterprise to compete in the market | Akça and Özer (2016) |
| | EF2 | BDPA is important to survive in the market | |
| | EF3 | Customers require BDPA adoption | |

# Appendix 2

## Sample of the questionnaire

How Can Big Data and Predictive Analytics Impact the Performance and Competitive Advantage of the Food Waste and Recycling Industry?

Since the advent of big data, numerous scientific and industrial domains have been able to make use of its positive effects. The waste management and recycling industries are ripe for the development of big data solutions to known problems. Hence, it is important to investigate how big data and predictive analytics can be adopted for recycling and waste management, as well as the impact of big data and predictive analytics on the performance of waste management and recycling industries. Accordingly, we are conducting this research entitled "How Can Big Data and Predictive Analytics Impact the Performance and Competitive Advantage of the Waste and Recycling Industry?" to investigate the aforementioned issue. This questionnaire is designed to gather information on the impacts of organizational, human, technological, and environmental factors on big data and predictive analytics adoption, the impact of big data and predictive analytics adoption on environmental and economic performance, and the impacts of environmental and economic performance on competitive advantage. Be assured that your responses to the questionnaire are for research purposes only, and will not be used outside of this study. We appreciate your participation in this study. If you need the research results, we will happily provide the study outcome. Your valuable response will help us complete this project.

## Demographic Questions

**1.** ***What is your gender?***

Female
Male

**2.** ***Please select your age group***
Under 25
25 – 34
35 – 44
45 – 54
55 – 64
65 and over

**3.** ***Educational Level***
Bachelor
Master
Ph.D.
Senior high school or below

**4.** ***Job Title***
IT Manager
Chief Executive Officer
Senior Manager
Mid-Level Manager
Director of Organization
Consultant

## Experience with Research Concepts

**5.** ***Work experience with the industry***
Less than 3 years
3-5 years
6-8 years
More than 8 years

**6.** ***Level of familiarity with Big Data and Predictive Analytics***
Low Familiarity
Moderate Familiarity
High Familiarity

## Organizational Factor (Top Management Support)

**7.** ***Top management understands the significance of BDPA***
Strongly Disagree
Disagree
Neutral
Agree
Strongly Agree

**8.** ***Top management actively deploys BDPA***
Strongly Disagree
Disagree
Neutral
Agree
Strongly Agree

**9.** ***Top management supports initiatives related to BDPA***
Strongly Disagree
Disagree
Neutral
Agree
Strongly Agree

### Human Factor (Knowledge)

**10.** ***Our employees have a high level of knowledge***
Strongly Disagree
Disagree
Neutral
Agree
Strongly Agree

**11.** ***Our employees have a high level of expertise***
Strongly Disagree
Disagree
Neutral
Agree
Strongly Agree
Strongly Agree

**12.** ***Our employees have a high level of technological knowledge***
Strongly Disagree
Disagree
Neutral
Agree
Strongly Agree

### Big Data and Predictive Analytics

**13.** ***Our enterprise intends to adopt BDPA in the future.***
Strongly Disagree
Disagree
Neutr
al
Agree
Strongly Agree

**14.** ***Our enterprise recommends BDPA to other enterprises.***
Strongly Disagree
Disagree
Neutral
Agree
Strongly Agree

**15.** ***Our enterprise follows the required strategies for the utilization of BDPA.***
Strongly Disagree
Disagree
Neutral
Agree
Strongly Agree

### Competitive Advantage

**16.** ***Our enterprise has a considerable advantage over other competitors.***
Strongly Disagree
Disagree
Neutral
Agree
Strongly Agree

**17.** ***Our enterprise has new standards in the area.****
Strongly Disagree
Disagree
Neutral
Agree
Strongly Agree

**18.** ***Our enterprise surpasses competitors in terms of innovation and technology****
Strongly Disagree
Disagree
Neutral
Agree
Strongly Agree

## Economic Performance

**Rate the economic performance of your organization in thefollowing aspects (1-5)**

**19.** ***Profit growth***
1
2
3
4
5

**20.** ***Added value***
1
2
3
4
5

**21.** ***Sales growth***
1
2
3
4
5

## Environmental Performance

**Rate the environmental performance of your organization in thefollowing aspects (1-5)**

**22.** ***Designing reusable products***
1
2
3
4
5

**23.** ***Regulating eco-friendly strategies***
1
2
3
4
5

**24.** ***Eco-friendly products and services***
1
2
3
4

## Technological Factor (Compatibility and Complexity)

**25.** ***Integrating BDPA tools in our enterprise's procedures is applicable***
Strongly Disagree
Disagree
Neutral
Agree
Strongly Agree

**26.** ***No complex skills are required for using BDPA***
Strongly Disagree
Disagree
Neutral
Agree
Strongly Agree

**27.** ***Using BDPA runs with our enterprise's procedures***
Strongly Disagree
Disagree
Neutral
Agree
Strongly Agree

**28.** ***Using BDPA runs with our enterprise's current technologies***
Strongly Disagree ☐
Disagree ☐
Neutral ☐
Agree ☐
Strongly Agree ☐

**29.** ***Using BDPA runs with our enterprise's aims and goals***
Strongly Disagree ☐
Disagree ☐
Neutral ☐
Agree ☐
Strongly Agree ☐

**Environmental Factor (Competitive Pressure)**

**30.** ***BDPA allows our enterprise to compete in the market***
Strongly Disagree ☐
Disagree ☐
Neutral ☐
Agree ☐
Strongly Agree ☐

**31.** ***BDPA is important to survive in the market***
Strongly Disagree ☐
Disagree ☐
Neutral ☐
Agree ☐
Strongly Agree ☐

**32.** ***Customers' requirements require the adoption of BDPA***
Strongly Disagree ☐
Disagree ☐
Neutral ☐
Agree ☐
Strongly Agree ☐

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