The Impact of Big Data Predictive Analytics on Firm Performance: The Role of Cloud ERP and Business Intelligence Integration

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Abstract

The purpose of this study was to investigate the relationship between Big Data Predictive Analytics (BDPA) dynamic capability and integration of cloud Enterprise Resource Planning (ERP) and Business Intelligence (BI) based on Technology-Organization-Environment (TOE) framework, and their impact on performance for Egyptian industrial organizations. The Survey was developed using constructs from previous studies that related to study variables, and it was then modified to fit needs of the study. A questionnaire list was utilized as the data collection instrument for a survey of 200 companies from various Egyptian industrial sectors, where the research hypothesis test was based on the method of structural equation modeling based on the partial least squares method based on variance to analyze data through "Smart-PLS" program, as this method is the most suitable for the characteristics of this research due to considerations of sample size and nature of data. The results indicated that a positive relationship between BDPA and the integration of BI and cloud ERP, as well as improving the Cloud ERP and BI integration have a moderate effect on both financial performance and operational performance in the Egyptian environment.

Keywords: Big Data Predictive Analytics; Cloud ERP; Business Intelligence; Firm Performance; Egyptian Industrial Organization

Introduction

Over the past two decades, the use of advanced digital technologies has led to a significant change in the way industrial organizations carry out their operations, given the great strategic importance of these technologies and their ability to make a difference in a highly competitive global market.

Although Business Intelligence (BI) systems have piqued the interest of executives and decision makers due to their ability to provide complex and competitive information inputs for decision making, organizations have largely failed to fully realize the benefits of BI systems and are looking for ways to leverage value from the implemented systems (Ain *et al.*, 2019), so more research into BI and its relationship with company performance is still required.

Cloud ERP, as opposed to on-premise ERP systems, is becoming the new trend in the ERP industry because to the benefits of economies of scale generated through pooled resources systems (Demi & Haddara, 2018). Despite the relevance of integration between BI systems and cloud ERP systems, studies on this subject have received insufficient attention (Nofal & Yusof, 2016).

Big data Predictive analytics (BDPA), on the other hand, is a hot research area right now and it has resulted in a digital revolution in the field of operations, it is critical for businesses, governments, and it can additionally be utilized to give recommendations for certain events. (Yadegaridehkordi *et al.*, 2018; Mohbey& Kumar, 2022).

Gupta *et al.*, (2019) emphasis on how cloud ERP and BDPA will affect a firm's performance. In addition to this effort, this study seeks to investigate the impact of BDPA on the performance of Egyptian industrial organizations via the cloud ERP and BI integration, as shown in Figure (1).

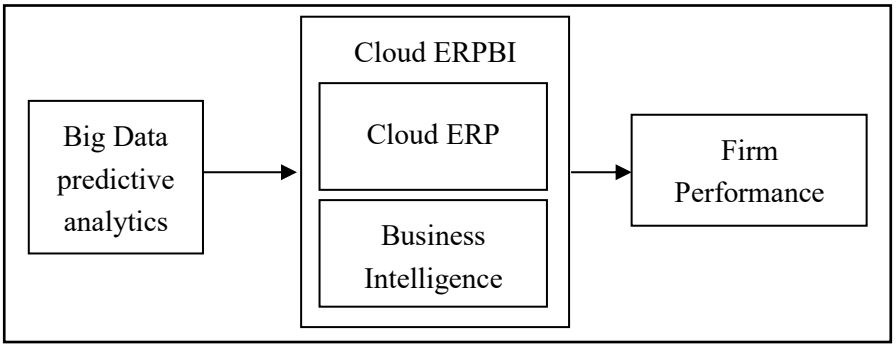

Figure (1) study framework

Source: *this study, In the light of the introduction*

Literature review

Cloud ERP and Cloud Computing

ERP system is a well-known and widely used corporate solution; it is a packaged business software solution that assists an organization in managing the efficient and effective use of resources such as supplies, human resources, and financing as well as performance improvements and cost savings (Dey *et al.*, 2010; Bahssas, 2018).

Cloud computing is a modern IT outsourcing model that enables organizations to utilize an assortment of third-party hosting IT resources and applications as virtual services via the web, without the need of physically storing these computing resources inside (Mell, 2011; Dutta *et al.*, 2013).

The three categories that depict the various forms of cloud computing services are Software as a Service (SaaS), Infrastructure as a Service (IaaS), and Platform as a Service (PaaS) (Musse *et al.,* 2016). Dillon and & Chang (2010) stated that it often involves different application domains such as ERP, customer relations management (CRM).

Implementing and operating ERP systems on the cloud provides numerous advantages and benefits (Abd Elmonem, *et al*, 2016).

Peng *et al.* (2014) defined Cloud ERP systems as "*an ERP application hosted through a third-party vendor managed and controlled infrastructure*" (p.22). It is possible to state that it a bundled business software system that employs cloud computing possibilities to help organizations manage the efficient and effective use of resources by providing a complete integrated solution for the organization's information processing needs Alsharari (2022).

ERP has grown into a cloud ERP as a result of current technology breakthroughs in cloud computing. In fact, on-premise ERP solutions force organizations to manage their own IT infrastructure, demanding significant hardware and software investments as well as ongoing maintenance costs. Cloud ERP solutions, on the other hand, offer the same functionality as on-premise ERPs at much lower costs because they are set up, maintained, and serviced remotely (Prakash *et al.*, 2022).

The Internet's availability and the improving stability of cloud infrastructure have made cloud ERP commercially viable and enabled it to increasingly replace traditional ERP (Razzaq& Mohammed, 2020), and it can provides more benefits such as simplicity of use and resource elasticity (Marinho *et al,* 2021).

Because ERP systems and cloud platforms are the sources of big data (Blazquez & Domenech, 2018), it is critical to address big data and its branching predictive data.

Big Data predictive analytics (BDPA)

Adoption of big data is becoming increasingly important for businesses and industries. It not only ensures a competitive advantage and increases marketing success, but it also reduces organizations' overall operational costs (Yadegaridehkordi *et al.*, 2018).

Big Data refers to large-volume, complicated, increasing data sets from various and independent sources; it is presently quickly developing across all science fields due to the rapid expansion of networking, data storage, and data collection capacity (Wu *et al.*, 2013).

Due to the changing nature of data and new technology, big data sources might be structured, unstructured, or semi-structured that comes from web, social media, and cloud ERP systems. It could be in a variety of shapes (text, message, graphic, audio, and video), this requires the use of unusual approaches to treat and benefit from it (Mohasseb, 2020; Bag *et al.*, 2021).

Predictive analytics is the process of forecasting future events based on previous data and analytics methodologies. It's a subset of data analytics. It employs a variety numerous tools and techniques of data mining, statistics, modeling, AI, and machine learning (Mohbey& Kumar, 2022).

BDPA is a new set of technologies that can store and handle massive amounts of data in real time at lower prices than ever before. It can be described as data and technology integration that accesses, integrates, and reports all available data by filtering, correlating, and reporting insights that are not achievable with previous data technologies (Singh *et al.*, 2022).

Predictive analytics, as a business intelligence trend, assist organizations in optimizing their operations by forecasting demand and optimizing inventory levels in order to achieve high-value decision making. It also aids in the identification of potential dangers and the implementation of preventative actions to mitigate them (Tavera Romero *et al.*, 2021; Bharadiya, 2023a).

Business Intelligence (BI)

BI platforms are increasingly being utilized as front-end interfaces for big data systems that incorporate both structured and unstructured data. Modern business intelligence software often has various connectivity options, allowing it to connect to a variety of data sources. This, combined with most BI tools' relatively basic user interface (UI), makes it an excellent fit for big data infrastructures (Stedman& Burns, 2020).

BI is referred to as "an umbrella" that is often used to represent the technology, applications, and processes for obtaining, storing, accessing, and analyzing data to assist users in making better decisions (Davenport *et al*, 2010).

BI encompasses a wide variety of software applications. Data visualization, Data warehousing, data mining, and On-Line Analytic Processing (OLAP) are examples of essential BI technologies that Provides the ability to reason around and grasp the meaning behind business information through discovery, analysis and ad hoc query (Negash, 2004; Lönnqvist & Pirttimäki, 2006; Olszak, 2014; Colmenares-Quintero *et al.*, 2021).

Big data as a source of BI can be processed in the following steps *Extraction* of information from numerous sources; *Transform* data into standard formats and apply business rules to map data to the warehouse schema. *Load* Data loading is used to put the cleansed data into the data warehouse (Bharadiya, 2023b).

BDPA, cloud ERP-BI integration, and Firm Performance

Yadegaridehkordi *et al.* (2018) identified the rank of significant factors influencing big data adoption, in turn, to predict the influence of big data adoption on manufacturing companies' performance. Matthias *et al.*, (2017) adoption and exploitation of BDPA would generate competitive advantages for a firm's performance improvement. Verma (2017) emphasize that the value and advantages of BDPA can have a favorable impact on a firm's performance.

Cloud computing facilitates collaboration among supply chain partners and improves the organization's performance (Subramanian *et al.* 2014; Radke & Tseng, 2015). Sharma & Shah (2015) investigate the influence of information technology (IT) and cloud-enabled services (cloud ERP) in improving supply chain productivity. Gupta *et al.* (2018) revealing the beneficial effects of cloud ERP on supply chain performance, in similar circumstance Gupta *et al.* (2020) study the underlying link between cloud ERP and aspects of long-term organizational performance.

Antoniadis *et al.* (2015) demonstrated the primary benefits that small medium enterprises (SME) can receive from the deployment and use of an ERP system, as well as the business intelligence capabilities. In the same context, Nofal & Yusof (2016) proposed a model that identify and link critical success factors (CSF) for the ERP and BI integration and its relationship to organizational performance. They claimed that firms can improve their overall organizational productivity and efficiency by improving their CSF detection, and ERP-BI usage practices. On the other hand Tong-On *et al.* (2021) look into BI activities employing data analytics and the impact on company performance.

TOE framework and dynamic capabilities

The TOE framework was developed by Tornatzky & Fleischer (1990) is a well-known model that suggests an overall set of factors that explain and forecast the likelihood of innovation and technology adoption and this process of adopting and implementing technological innovations is affected by the technological, organizational, and environmental context, according to this theoretical framework that explains how it occurs in organizations.

According to Liu (2019), the term "technological context" refers to both current and emerging technologies that are pertinent to the company. The term "organizational context" relates to characteristics of the organization, such as its scope, size, organizational structure, level of financial support, managerial assumptions, and support from the top management. The term "environmental context" is the field in which a company operates, which includes its industry, technology support infrastructure, and government regulation.

This framework is consistent with the Diffusion of Innovations Theory (DOI), However, the TOE premise is comparable to Actor Network Theory (ANT) in that it emphasizes dynamic capabilities and the mutual interplay of technological and social systems (Awa *et al.*, 2016).

Teece *et al.* (1997) defined dynamic *capabilities* as *"the firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments"* (p.516).

Arifin (2015) employs the TOE framework to investigate the influence of dynamic capacities associated with technology adoption on company performance, with an emphasis on the determinants of technology adoption.

Gupta *et al.* (2019) identified dynamic BDPA capabilities through three resources, particularly (data, managerial skills, and technical skills). Similarly, for cloud ERP, there were three resources of dynamic capacities (organizational factors, human factors, and technology factors), as well as an explanation of their impact on the overall performance of the organization.

In contrast to Gupta *et al.* (2019), AlBar & Hoque (2019) used a DOI and TOE methodology to identify the factors that drive cloud ERP system adoption based on three components (organizational factors, environmental factors, and technological factors).

According to the preceding discussion, this research can thus rely on three basic dynamic capabilities, which are organizational, environmental, and technological, for the integration of BI and cloud ERP, as well as three other dynamic capabilities, which are data, managerial, and technical skill for BDPA.

Research questions and objectives

This study's goal was to look into the relationship between BDPA and integration of cloud ERP and BI dynamic capabilities depending on the TOE framework, as well as their effects on firm performance in the Egyptian environment.

Therefore, this study will address the following questions:

i. *How does the BDPA capability affect both BI and cloud ERP, and what effect does this have on the performance of Egyptian industrial organizations?*

ii. *What is the indirect influence of the BDPA capability on the performance of Egyptian industrial organizations?*

iii. *How can BI and cloud ERP capability affect the performance of Egyptian industrial organizations?*

Contribution to current knowledge

Previous studies have suggested a link between cloud ERP and organizational performance when BDPA is present, furthermore, studies reveals that Integration of cloud ERP with BI may have an impact on organizational performance excluding the effect of BDPA. Accordingly, this study motivated to examine and evaluate the adverse impacts of the relationship between BDPA and cloud ERP on the performance of the organization in the midst of BI based on TOE framework, since these variables are being addressed for the first time with this form of analysis.

Research Methodology

Hypotheses

The empirical nature of this study originates from its objectives. As a result, it is critical to examine the relationship between BDPA and cloud ERP and BI integration, as well as their consequences on firm performance, in order to shed light on the situation of Egyptian manufacturing companies; thus, the following hypotheses must be considered:

H1. BDPA capability have a significant impact on cloud ERP-BI integration.

H2. BDPA capability have a significant impact on operational performance.

H3. BDPA capability have a significant impact on financial performance.

H4. The integration between cloud ERP and BI capability have a significant impact on operational performance.

H5. The integration between cloud ERP and BI capability have a significant impact on financial performance.

H6. The integration of cloud ERP and BI mediates the relationship between BDPA capabilities and financial performance.

H7. The integration of cloud ERP and BI mediates the relationship between BDPA capabilities and operational performance.

Figure (2) shows that BDPA dynamic capabilities based on resources such as data, managerial skills, and technical skills have impact on integration of CERP and BI. Similarly, dynamic capabilities that are categorized into people, organizational, and technological factors constitute integration of CERP and BI dynamic capabilities, which affects a firm performance.

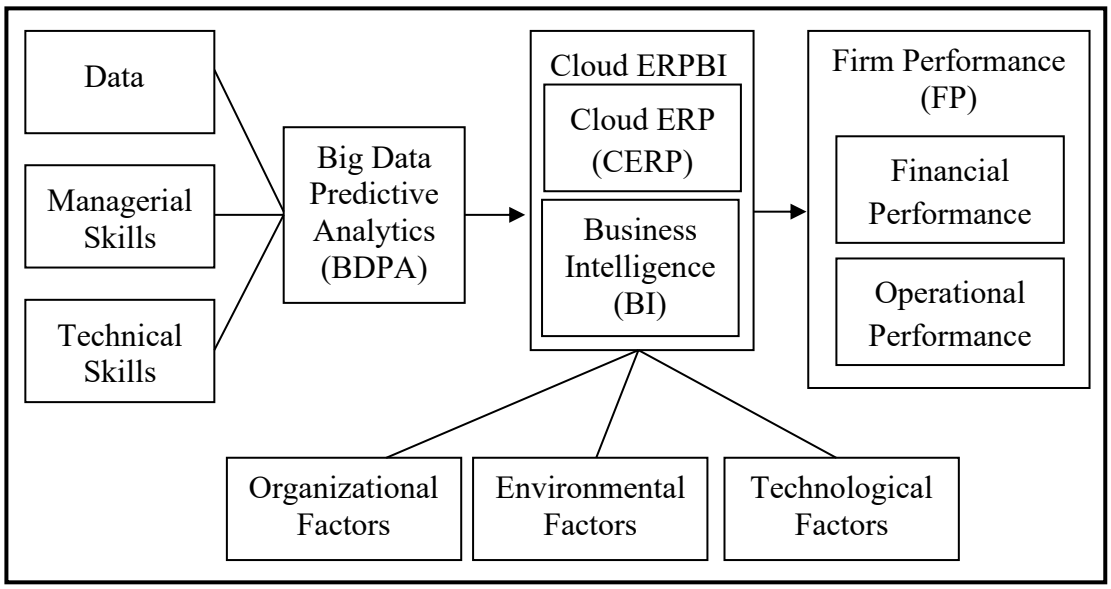

Figure (2) Proposed Study Model

SEM-PLS as a method of analysis

Testing the study hypotheses rely on the structural equation modeling approach based on the Variance-Based Partial Least Squares SEM (PLS-SEM) to analyze the data through Smart-PLS program, as this method is the most appropriate for the characteristics of this research due to considerations of sample size and the nature of the data (Hair, *et al.*, 2014).

The minimum appropriate sample size for the (PLS-SEM) methodology

i. The research relies on the formation of a constructive model that includes four latent variables, all of which contain reflective indicators, including three structural paths.

ii. Suitable size of sample for the proposed model can be calculated according to "ten times rule" which was declared by (Hair *et al.*, 2011; Peng & Lai, 2012) through the following steps:

   a. The number of structural paths in the model proposed in the research = 3 paths.

   b. 3 paths × 10 = 30 elements.

   c. So, the expected size of the sample size is at least 30 elements.

   d. Therefore, the number of research elements is suitable for building the proposed model, as the number of elements is 96, which is greater than 30 elements (expected size).

Scales and Measurement Tools

The first section of questionnaire list was based on the scale developed by Gupta *et al.* (2019). However, since the research was based on the TOE framework, the environmental factor was prioritized over the people factor , as reliance was placed on the set of elements that represent the environmental factor, which Liu (2019) adopted based on Tornatzky & Fleischer (1990). The questionnaire has a five-point Likert scale and is designed as follows: (1 = Not important at all; 2 = Not important; 3 = Neutral; 4 = Important; and 5 = Very important).

The second section of questionnaire contained items that used for measuring firm performance. It was built on a set of factors that considers operational performance and financial performance based on Gupta et al. (2019) scale, respectively: productivity has exceeded compared to competitors; profit rate has exceeded compared to competitors; return on investment has exceeded compared to competitors; sales revenue has exceeded compared to competitors; average return on investment; average return on investment; average profit; profit growth. (Responses are given on a five-point Likert scale, according to the opinion of the respondent, where 5 = strongly agree to 1 = strongly disagree).

Data collection

The data was gathered using a questionnaire list that was personally and electronically distributed to production and finance managers in the factories under study. The questionnaire list included 36 statements, 16 for measuring the variable "Cloud ERP-BI" and 13 for measuring the variable "BDPA" There are 4 phrases to measure "Operational Performance," 3 phrases to measure "Financial Performance," and 3 items to determine the type, size, and production system used by the companies and factories in question.

The questionnaire forms were distributed in early August 2023, the first set of responses were not received until late September 2023. To obtain the highest possible response rate, the questionnaires were also re-sent electronically - via "WhatsApp" program according to the numbers attached to the industries guide, by attaching the link to the questionnaire prepared by "Google form"-. Another group of responses was received between the beginning of October and the middle of November 2023. With a response rate of about 48%, 96 questionnaires were obtained that were valid for statistical analysis.

Research sample

A random sample of (200) elements was chosen from various Egyptian industrial sectors, which is the statistically required size with confidence level (95%) and a standard error (5%), as specified in the electronic tables created for this purpose. The questionnaires have been distributed to managers and staff members in the departments of operations and finance as table number (1) represents.

The Egyptian Industries Directory, which has 412 registered businesses, along with the databases of the General Authority for Industrial Development and the Federation of Egyptian Industries were used to identify the research population.

Table (1) Research sample

Sent questionnaires	200
Total responses	98
Final usable responses	96
Response rate as a percentage of sent questionnaires	48%

Descriptive statistics

Description	Less than 10	Less than 200	Bigger than 200
Employee number (size)	20.83%	34.38%	44.79%
	20	33	43
Description	**Private sector**	**Public sector**	**Multi-national**
Type of ownership	64.58%	29.17%	6.25%
	62	28	6
Description	**Batch**	**Continuous**	**Assembly**
production system	52.08%	20.83%	27.08%
	50	20	26

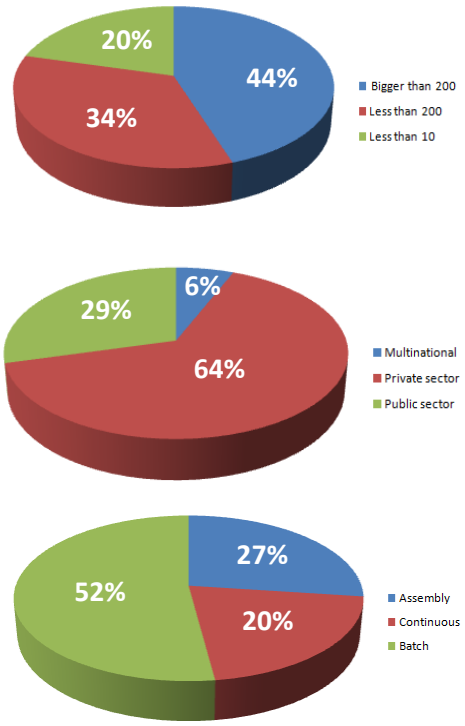

Figure (3) companies' size, production system, and type of ownership percentage

Observed Variables test

Convergent Validity

Indicators Loading

Table (2) indicators loading, composite reliability and AVE testing results

Variable Name	Items	Loading	Composite Reliability	Average Variance Extracted (AVE)
Data	D1	0.730	0.806	0.583
	D2	0.679		
	D3	0.869		
Managerial Skills	MS1	0.716	0.868	0.626
	MS2	0.826		
	MS3	0.923		
	MS5	0.676		
Technical Skills	TS1	0.809	0.926	0.715
	TS2	0.928		
	TS3	0.796		
	TS4	0.910		
	TS5	0.776		
Organizational Factors	OF2	0.632	0.812	0.530
	OF4	0.794		
	OF5	0.524		
	OF7	0.901		
Environmental Factors	EF1	0.819	0.843	0.524
	EF2	0.785		
	EF3	0.723		
	EF4	0.522		
	EF5	0.733		
Technological Factors	TF1	0.818	0.938	0.790
	TF2	0.880		
	TF3	0.959		
	TF4	0.894		
Operational Performance	OP1	0.937	0.898	0.696
	OP2	0.867		
	OP3	0.904		
	OP4	0.576		
Financial performance	FP1	0.860	0.897	0.743
	FP2	0.908		
	FP3	0.817		

Discriminant Validity

Cross Loadings

Discriminant validity expresses the extent to which a construct actually differs from other constructs by empirical standards (Hair *et al.*, 2014, p. 104), as there are two methods for analyzing Discriminant validity when evaluating reflective measurement models, namely the Fornell-larcker criterion and Cross Loadings. (Hair *et al.*, 2014, p. 100; Hair *et al.*, 2011, p. 146).

Table (3) Cross Loadings Testing Result

Items	Data	Manag-erial Skills	Techni-cal Skills	Organi-zational Factors	Enviro-nmental Factors	Techn-ological Factors	Operat-ional Perfor-mance	Financial perfor-mance
D1	0.730	0.466	0.327	0.010	0.324	0.169	0.155	0.074
D2	0.679	0.226	0.268	-0.154	0.422	0.184	0.227	0.303
D3	0.869	0.644	0.544	0.116	0.452	0.308	0.387	0.475
MS1	0.369	0.716	0.335	0.264	0.511	0.527	0.356	0.365
MS2	0.442	0.826	0.314	0.029	0.328	0.288	0.284	0.448
MS3	0.662	0.923	0.521	0.168	0.493	0.443	0.364	0.526
MS5	0.478	0.676	0.074	0.100	0.305	0.046	0.076	0.285
TS1	0.352	0.340	0.809	0.180	0.624	0.481	0.388	0.545
TS2	0.364	0.359	0.928	0.426	0.747	0.603	0.468	0.595
TS3	0.422	0.334	0.796	0.402	0.524	0.318	0.399	0.503
TS4	0.365	0.458	0.910	0.369	0.548	0.412	0.345	0.477
TS5	0.702	0.333	0.776	0.217	0.539	0.455	0.549	0.540
OF2	-0.131	0.057	0.275	0.632	0.217	0.273	0.166	0.235
OF4	0.110	0.181	0.279	0.794	0.222	0.261	0.220	0.230
OF5	-0.007	-0.054	0.098	0.524	0.063	0.101	0.076	-0.001
OF7	0.056	0.214	0.365	0.901	0.422	0.501	0.365	0.365
EF1	0.265	0.397	0.431	0.390	0.819	0.345	0.283	0.374
EF2	0.380	0.438	0.371	0.217	0.785	0.626	0.747	0.640
EF3	0.069	0.237	0.408	0.211	0.723	0.639	0.314	0.261
EF4	0.302	0.333	0.376	0.217	0.522	0.455	0.510	0.519
EF5	0.317	0.306	0.343	0.185	0.733	0.490	0.108	0.164
TF1	0.315	0.401	0.522	0.258	0.601	0.818	0.648	0.456
TF2	0.151	0.294	0.390	0.454	0.642	0.880	0.605	0.397
TF3	0.342	0.443	0.448	0.346	0.811	0.959	0.600	0.535
TF4	0.262	0.434	0.561	0.506	0.800	0.894	0.585	0.626
OP1	0.354	0.289	0.405	0.183	0.608	0.629	0.937	0.644
OP2	0.255	0.254	0.369	0.185	0.533	0.591	0.867	0.630
OP3	0.363	0.306	0.515	0.269	0.623	0.646	0.904	0.788
OP4	0.245	0.399	0.404	0.516	0.346	0.365	0.576	0.379
FP1	0.399	0.427	0.545	0.275	0.500	0.529	0.749	0.860
FP2	0.281	0.421	0.483	0.406	0.538	0.531	0.734	0.908
FP3	0.352	0.538	0.615	0.168	0.587	0.4050	0.441	0.817

i. Examining the reliability values of each item, table (2) revealed that one of the items (item MS4 with the "managerial skills" variable) did not achieve the required reliability value of 0.093, as did the items (OF1 - OF2 - OF3) with the "organizational factor" variable. The required reliability values (0.194 - 0.041 - 0.279) were not met because the specified range of reliability for each item must be greater than or equal to 0.70 and less than 0.95.

ii. The element that did not achieve the required reliability value was excluded, with the exclusion not exceeding the permissible limit of 20% of the total number of elements in the research model, (4 ÷ 32) * 100 = 11.11%.

iii. Table (2) displays the reliability values after re-analysis, excluding the elements that did not achieve the required value.

iv. By examining the reliability values of each item, we discover that the group of items (MS5) (OF2 – OF5) (EF4) (OP4) did not achieve the required reliability values, and they were kept because they fall in the range of 0.40 to 0.70, and when excluded, they did not change the minimum values of composite reliability or average variance extracted for a variable.

v. All components of the composite reliability for all variables are greater than 0.70, and all components of the average variance extracted (AVE) are greater than 0.50, indicating convergence of all elements of the research model and qualifying them for Discriminant validity analysis.

vi. Examining the values in Table (3), we discover that the value of each element for each variable in the model is recorded as the largest value that falls within the range of this element in relation to all other variables in the model, indicating the differentiation and non-overlapping of each element of the model for each variable.

vii. We can see from the values in the following table that the value at the intersection of each variable with itself represents the largest value in its horizontal and vertical range (the largest value in relation to other variables). For example, the "financial performance" variable has a value of 0.862, which is the highest value in the variable's horizontal range. (0.862 > 0.727), (0.862 > 0.396), and it is also the largest value in the variable's vertical range (0.862 > 0.531), (0.862 > 0.334), (0.862 > 0.751), (0.862 > 0.569), and so on for the remaining values in the table (4).

Discriminant Validity

Fornell-larcker criterion

Table (4) Fornell-larcker criterion Testing Result

Variables	Data	Enviro-nmental Factors	Financ-ial perfor-mance	Manag-erial Skills	Organi-zational Factors	Operat-ional Perform ance	Techno-logical Factors	Techni-cal Skills
Data	**0.764**							
Environmental Factors	0.526	**0.774**						
Financial performance	0.396	0.727	**0.862**					
Managerial Skills	0.627	0.623	0.531	**0.791**				
Organizational Factors	0.019	0.453	0.334	0.176	**0.727**			
Operational Performance	0.371	0.695	0.751	0.369	0.331	**0.834**		
Technological Factors	0.300	0.738	0.569	0.442	0.444	0.680	**0.889**	
Technical Skills	0.526	0.638	0.630	0.433	0.380	0.512	0.538	**0.846**

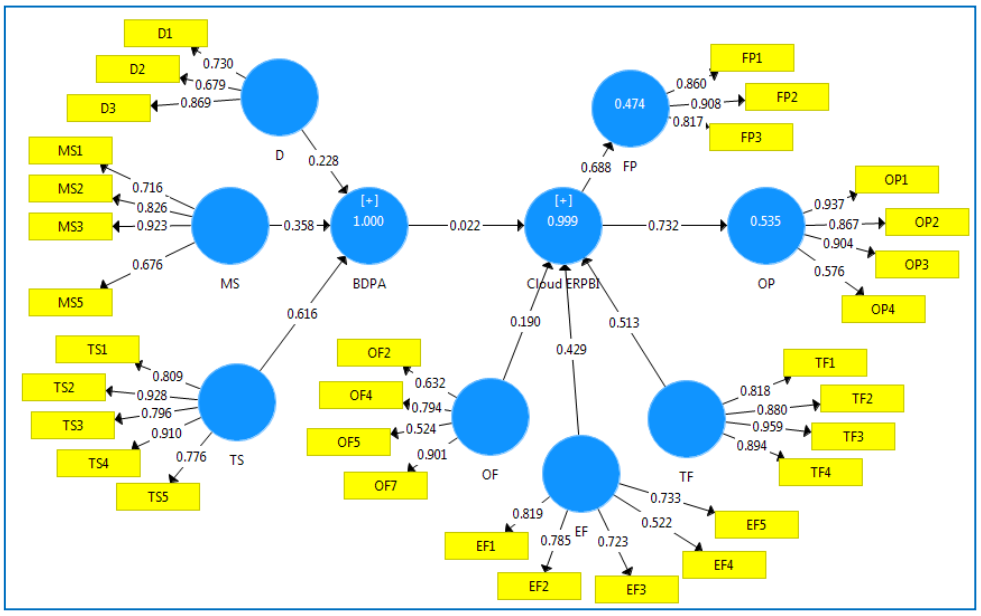

Figure (2): reliability of each indicator of the research model
Source: Smart-PLS output

Assessment of Structural Model (Testing hypotheses)

Testing Hypotheses (H1:H5)

A significance level of less than 0.05, less than 0.01 and positive β values are reached, indicating a positive correlation, whether direct or indirect, between the research variables as shown in table (5).

Table (5) research variables significance

Research variables relationships	β Beta	STD. Error	T	sig.
BDPA → Cloud ERPBI	**0.013**	**0.015**	**2.109**	**0.035**
Cloud ERPBI → Financial Performance	**0.643**	**0.651**	**13.545**	**0.000**
Cloud ERPBI → Operational Performance	**0.715**	**0.721**	**16.226**	**0.000**
BDPA → Financial Performance	**0.020**	**0.009**	**2.216**	**0.027**
BDPA → Operational Performance	**0.022**	**0.010**	**2.243**	**0.025**

Table (6) hypotheses testing results

Hypothesis	*p*-value	Supported / not supported
BDPA → Cloud ERPBI	**< 0.05**	**Supported**
Cloud ERPBI → Financial Performance	**< 0.01**	**Supported**
Cloud ERPBI → Operational Performance	**< 0.01**	**Supported**
BDPA → Financial Performance	**< 0.05**	**Supported**
BDPA → Operational Performance	**< 0.05**	**Supported**

Since all research hypotheses are supported by significance levels of 0.05 and 0.01, the effect size for both independent and dependent variables can be determined as shown in tables (7) and (8).

Table (7) size effect on Financial Performance and Operational Performance

Variable	R^2	Result
Financial Performance	**0.474**	Moderate
Operational Performance	**0.535**	Moderate

According to table (7), the integration between BI and Cloud ERP is responsible for approximately 47% of the change in the financial performance of Egyptian industrial companies. Furthermore, the integration of BI and Cloud ERP accounts for approximately 54% of the change in operational performance of Egyptian industrial companies.

Table (8) size effect of BDPA on Cloud ERPBI

Variable	F^2	Result
BDPA → Cloud ERPBI	**0.322**	Medium

Cloud ERP and BI integration have a moderate effect on both financial performance and operational performance, furthermore the effect size of BDPA on cloud ERP and BI integration are medium, according to Chin (1998) the value of R^2 that above 0.67 considered high, while values ranging from 0.33 to 0.67 are moderate whereas values between 0.19 and 0.33 are weak and any R^2 values less than 0.19 are unacceptable. The values of F^2 above 0.35 considered large effect size while values ranging from 0.15 to 0.35 are medium effect size, whereas values between 0.02 to 0.15 considered small effects, finally F^2 values less than 0.02 are considering with no affect size.

Testing Hypotheses (H6-H7)

According to Preacher & Hayes (2008) approach, the mediation was evaluated by first calculating the bootstrap indirect impact and then calculating the bootstrapped confidence interval as follows:

Table (9) Mediation variables Confidence Interval

BDPA ↓ Cloud RPBI	Cloud ERPBI ↓ Financial Performance				Bootstrapped Confidence Interval	
Path A	**Path B**	**Indirect Effect**	**SE**	**T-Value**	**95% LL**	**95% UL**
0.310	**0.643**	**0.199**	**0.009**	**2.176**	**0.1817**	**0.21697**

i. Path "A": The value of the effect between the independent variable (BDPA) and the mediating variable (Cloud RPBI integration).

ii. Path "B": The value of the effect between the mediating variable (Cloud RPBI integration) and the dependent variable (Financial Performance).

iii. Indirect effect: the product of multiplying the value of path "A" by the value of path "B".

iv. Minimum level: It is calculated through the following equation:

a. The value of the indirect effect - (1.96 × standard deviation).

v. The highest level: It is calculated through the following equation:

a. The value of the indirect effect + (1.96 × standard deviation).

vi. The value of the lower level is **0.1817** and the value of the upper level is **0.21697**

vii. The absence of a zero intersection between the two numbers indicates the validity of the **presence of the mediating variable**.

Table (10) Mediation variables Confidence Interval

BDPA ↓ Cloud RPBI	Cloud ERPBI ↓ Operational Performance				Bootstrapped Confidence Interval	
Path A	Path B	Indirect Effect	SE	T-Value	95% LL	95% UL
0.310	0.715	0.222	0.100	2.228	0.0257	0.41765

i. Path "A": The value of the effect between the independent variable (BDPA) and the mediating variable (Cloud RPBI integration).

ii. Path "B": The value of the effect between the mediating variable (Cloud RPBI integration) and the dependent variable (Operational Performance).

iii. Indirect effect: the product of multiplying the value of path "A" by the value of path "B".

iv. Minimum level: It is calculated through the following equation:

a. The value of the indirect effect - (1.96 × standard deviation).

v. The highest level: It is calculated through the following equation:

a. The value of the indirect effect + (1.96 × standard deviation).

vi. The value of the lower level is **0.0257** and the value of the upper level is **0.41765**

vii. The absence of a zero intersection between the two numbers indicates the validity of the **presence of the mediating variable**.

Discussion and Conclusion

Although many studies have addressed the issue of the relationship between BDPA and cloud ERP and their joint impact on company performance, this study discussed this relationship in a new framework that includes understanding the adverse effect of the relationship between BDPA and cloud ERP with regard to BI and cloud ERP integration in the context of TOE framework and dynamic capabilities, as the research results revealed a positive, significant relationship between BDPA and the integration of BI and cloud ERP, as well as the emergence of a significant effect of BDPA on the integration of BI and cloud ERP.

The findings also revealed that the integration of BI with cloud ERP has a beneficial influence on the firm performance; whether financial or operational, as well as the appearance of an indirect impact of BDPA on the firm performance, Considering that the impact of integrating BI and cloud ERP on operational performance was larger than the impact on financial performance, and that both effects are deemed to be moderate, the effect of BDPA on this integration is likewise deemed to be moderate. Furthermore, there is a significant indirect effect of BDPA on both operational and financial performance within the Egyptian industrial environment. This result supported by (Verma, 2017; Matthias *et al.*, 2017; Gupta *et al.*, 2019).

Overall, our findings coincide with (Teece *et al.*, 1997; Smith *et al.* 2014) regarding the firm's performance, as well as Gupta *et al.* (2019) on the company's operational performance and Gupta *et al.* (2018) on the company's financial performance. It also concurs with (Nofal & Yusof, 2016; Zheng & Khalid, 2022) regarding the integration of BI and cloud ERP and the influence on firm's performance and business continuity.

Furthermore, the investigation revealed that the BDPA capability has an indirect impact on the organization's financial and operational performance through BI and cloud ERP integration as a mediator variable. This result is significant in terms of the need to support the BDPA capabilities by conducting further integration between BI and cloud ERP, both at the technological, environmental, and organisational levels, with the goal of improving the Egyptian organization's financial and operational performance.

On the other hand, the study's findings show that, when it comes to the study's sample, the private sector is more represented than both public sector organizations and multinational corporations. The Egyptian government intentions for privatization and the public sector's limited participation in industrial processes may be the cause of this. Moreover, the batch production system exceeded both the continuous and assembly production systems in terms of sample representation for the study and the proportion of small companies in the research sample was the lowest, when it came to the number of employees, large companies had the highest representation in the sample, followed by medium-sized companies.

Managerial Implications

Previous investigation indicates that the following managerial adjustments have to be made by Egyptian decision-makers, managers, producers, and government representatives:

Since this study explained the relationship between BDPA and the integration of BI and cloud ERP and its positive impact on company performance, company managers and manufacturers in Egyptian industrial organizations must pay attention to supporting the technological, environmental, and organizational factors that would help increase and raise this influence.

The positive impact of BDPA on the integration of BI and cloud ERP motivates Egyptian manufacturers to provide data and technical support, as well as develop individuals' skills, in order to deepen this benefit, especially as it affects both the company's financial and operational performance, thus supporting the company's competitiveness and achieving long-term cost savings.

Directions for Future Research

Additional study on this critical issue can widen the scope of the examination. Despite the fact that the current study focused on the link between BDPA and the integration of BI and cloud ERP, as well as its beneficial influence on firm performance, however, some organizational and personal factors, such as organizational culture and confronting pressures, can be introduced as mediating variables and the degree of their effect on those variables can be measured.

The variables of this research can also be discussed in a wider context by examining them from a socio-technical perspective, which includes social, organizational, and environmental factors. We can then measure the influence of these factors on the competitiveness and performance of the organization, giving us a more comprehensive understanding of their effects.

Lastly, since some technological factors may not be equally important in different countries, more research of a similar nature could be carried out in other developing nations, enabling us to conduct comparative studies with those nations to ascertain the similarities and differences regarding cloud ERP and BI integration in order to examine these technologies in different contexts.

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Appendix

1-Data on the type and size of the company, as well as the production system used by the organization to which you belong

	Less than 10	Less than 200	Bigger than 200
Firm size			

	Private sector	Public sector	Multi-national
Firm type			

	Batch	Continuous	Assembly
Production system			

2- How important are the following elements are for developing integration between cloud ERP and business intelligence?

Phrase		Very important	important	Neutral	Not important	Not important at all
Organizational Factors						
2/1	Strategic goals and objectives					
2/2	Communication					
2/3	Implementation strategy					
2/4	Business process re-engineering					
2/5	Project management					
2/6	Project budget					
2/7	Organization resistance					
Environmental Factors						
2/8	Technology support infrastructure					
2/9	Industry characteristics					
2/10	Regulation					

2/11 Selection of vendor					
2/12 Trust on vendor					
Technological Factors					
2/13 Selection of ERP package					
2/14 IT infrastructure					
2/15 Data integrity and system testing					
2/16 Functionality					

3- To what extent do the following elements demonstrate the degree of implementation of big data predictive analytics?

Phrase	Strongly agree	agree	Neither agree nor disagree	disagree	Strongly disagree
Data					
3/1 Access to very large, unstructured, or fast-moving data for analysis					
3/2 Integrate data from multiple internal sources into a data warehouse for easy access					
3/3 Integrate external data with internal to facilitate high-value analysis of business environment					
Managerial skills					
3/4 Big data analytics managers are able to					

work with functional managers, suppliers and customers					
3/5 Big data analytics managers are able to coordinate big data-related activities					
3/6 Big data analytics managers are able to anticipate the future business needs					
3/7 Big data analytics managers have a good sense of where to apply big data					
3/8 Big data analytics managers are able to understand and evaluate the output extracted from big data					
Technical skills					
3/9 Big data analytics training to employees					
3/10 Hire new employees that already have the big data analytics skills					
3/11 Big data analytics staff has the right skills to accomplish their jobs successfully					

3/12	Big data analytics staff has suitable education to fulfill their jobs					
3/13	Big data analytics staff holds suitable work experience to accomplish their jobs successfully					

4- The following tangible performance improvements are achieved as a result of the integration of cloud ERP with business intelligence.

Phrase		Strongly agree	agree	Neither agree nor disagree	disagree	Strongly disagree
Operational Performance						
4/1	Productivity has exceeded compared to competitors					
4/2	Profit rate has exceeded compared to competitors					
4/3	Return on investment (ROI) has exceeded compared to competitors					
4/4	Sales revenue has exceeded compared to competitors					
Financial Performance						
4/5	Average return on investment					
4/6	Average profit					
4/7	Profit growth					

أثير التحليلات التنبؤية للبيانات الضخمة على أداء الشركة: دور التكامل بين تخطيط موارد المشروع القائم على الحوسبة السحابية وذكاء الأعمال

د. أيمن محمد محسب

المستخلص

الغرض من هذه الدراسة هو دراسة العلاقة بين القدرة الديناميكية للتحليلات التنبؤية للبيانات الضخمة (BDPA) وتكامل تخطيط موارد المشروع القائم على الحوسبة السحابية (Cloud ERP) وذكاء الأعمال (BI) استنادًا إلى إطار عمل "التكنولوجيا والمنظمة والبيئة" (TOE)، وأثرهما على أداء المنظمات الصناعية المصرية. تم إجراء البحث باستخدام بناءات (Constructs) من الدراسات السابقة المتعلقة بمتغيرات الدراسة، ومن ثم تم تعديلها لتناسب احتياجات الدراسة. تم استخدام قائمة الاستبيان كأداة لجمع البيانات لمسح ٢٠٠ شركة من مختلف القطاعات الصناعية المصرية، حيث اعتمد اختبار فروض البحث على أسلوب نمذجة المعادلات الهيكلية المعتمدة على المربعات الصغرى الجزئية القائمة على التباين لتحليل البيانات من خلال برنامج "Smart-PLS"، حيث تعتبر هذه الطريقة هي الأنسب لخصائص هذا البحث نظراً لاعتبارات حجم العينة وطبيعة البيانات. أشارت النتائج إلى إيجابية العلاقة بين قدرات التحليلات التنبؤية للبيانات الضخمة وتكامل تخطيط موارد المشروع القائم على الحوسبة السحابية مع ذكاء الأعمال، كذلك أظهرت النتائج أن تحسين تكامل تخطيط موارد المشروع القائم على الحوسبة السحابية مع ذكاء الأعمال له تأثير معتدل على كل من الأداء المالي والأداء التشغيلي في البيئة المصرية.

الكلمات المفتاحية: التحليلات التنبؤية للبيانات الضخمة؛ تخطيط موارد المشروع القائم على الحوسبة السحابية؛ ذكاء الأعمال؛ أداء الشركة؛ المنظمات الصناعية المصرية.