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Examining the Relationship Between Enterprise Resource Planning (ERP) Implementation: The Role ofBig Data Analytics Capabilities and Firm Performance

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Abstract

Enterprise Resource Planning (ERP) implementation continues to hold attraction from information systems enthusiasts. Perhaps due to the rising budget dedicated to the implementation in many an organization in recent times. However, understanding the critical role that ERP implementation plays in Big Data Analytics Capabilities and firm performance is lacking sufficient treatment in the literature. By applying quantitative research techniques in a case study research orientation through the use of resource-based view theoretical insights, the study takes on three key hypotheses: That ERP implementation has a positive relationship with organizational big data analytics capabilities; Big data analytics capability has a positive effect on firm performance and ERP implementation is positively related to organizational performance. Using Partial Least Squared Structural Equation Model (PLS-SEM) data analysis techniques the study established a direct link between big data analytics capabilities and firm performance, and that ERP has a direct positive and significant effect on big data analytics capabilities. Lastly, it is the claim of this study that big data analytics capabilities have a direct positive and significant effect on firm performance. Part of the implications of the study highlights the need for a qualitative or even mixed method research undertakings to broaden the frontiers of our understanding in terms of ERP implementation and big data analytics capabilities in similar organizational contexts.

1. Background

For organizations to survive in today's competitive business environment, the application of creative and innovative ideas and strategies become essential (Al-Dhaafri, Al-Swidi, and Yusoff, 2016). Following the benefits of IS as touted by professionals and scholars alike (Shang and Seddon, 2000; Staehr, Shanks and Seddon, 2012; Althunibat et al., 2019), several organizations have decided to invest in the adoption of Enterprise Resource Planning (ERP) to enhance their business processes and improve their performance. The study focuses on organizations with ERP implementation experience. The subject of interest in this case is manufacturing and service organizations. The essence of this subject of interest is to develop a research model that validates primary data collected from firms in Kumasi and Accra. The choice of Kumasi and Accra is because of its geographical proximity and also due to the fact these two cities are have a number of large organizations that are heavily involved with the implementation of ERP systems in recent times.

The Enterprise Resource Planning (ERP) is an information system helps firms to achieve their need for an integrated organization (Madapusi and D'Souza, 2012; Rupa, Rao and Babu, 2019; Shah et al., 2011). ERP has been in existence for over 30 years and its adoption within organizations continues to increase (Eker and Aytaç, 2016).

Many have touted the favourable uses of ERP systems as aiding the solution of the challenges in business systems fragmentation (Kashani, 2014) that results in duplication of information, data redundancy and difficulty in information sharing across the organization. The integrative nature of ERP allows organizations to enhance its information processing, decision making and innovation capabilities (Ram, Corkindale and Wu, 2014). With the innovation capabilities, the advent of social media and cloud computing systems have seen the trend for firms to integrate their ERP systems with social media and move their ERP-applications and databases into the cloud (Gupta, Qian, Bhushan and Luo, 2019).

Large volumes of diverse data sets entering an organization at an increased speed is referred to as big data (Gandomi, and Haider, 2015). Akter et al. (2016) also explains that big data analytics capability refers to the ability to manage big data for useful business insights. While ERP implementation has the prospect to enhance big data analytics capabilities of organizations, some studies have acknowledged that big data capability plays a key role in improving the performance of organizations (Akter et al., 2016). The study hypothesizes the point that ERP implementation has a direct positive effect on organizational big data capabilities and also firm performance. Again, the study hypothesizes the idea that big data analytics capabilities has a direct positive effect on firm performance and also meditates the relationship between ERP implementation and firm performance.

Madhani (2009) contends that distinguishing between sources that offer success and those that provide sustainability is very challenging. Therefore, it is necessary to make a significant managerial effort to identify, classify, and understand these resources that offer core competencies, sustainability, and competitive advantage. In view of this, the resource-based view theory is applied to tease out the ideals of this study. Drawing on this theory, this study specifically examines the direct effect of ERP implementation on organizational Big Data capabilities. In doing this, the study explains how well ERP implementation affects BDA capabilities and performance of organizations. In addition, this research aims to examine the effect of ERP implementation on organizational big data analytic capabilities, ascertain the effect of ERP implementation on firm performance and determine the effect of big data analytics capabilities on firm performance. Doing this is designed to make some contribution to not only knowledge but also in terms of practice. This claim is grounded in the call to address the mechanisms by which ERP implementation influence firm performance through the examination of the link between ERP implementation, BDA capability and the performance of firms (Al-Dhaafri et al.'s 2016; Elragal's 2014).

The rest of the paper proceeds as follows. After this introduction, the next section reviews the contemporary account on ERP systems in terms of both their theoretical and practical perspectives. The methods that guided the study comes next with the sampling techniques as wells the design approach that motivated the sampling techniques for data collection and analysis. Findings from the study are presented for analysis and research implications are briefly discussed to conclude the paper.

2. **ERP Implementation and Big Data Analytics**

The ERP has been developed through the growth and expansion of the Manufacturing Resource Planning (MRP II) and the Material Requirement Planning (MRP) (Abdullah 2017; Elmes et al., 2005). In the 1980s, MRP evolved from control and material planning to a firm-wide program capable of planning and controlling almost all organizational resources (Chen, 2001; Miclo et al., 2017; Soja, 2008). MRP progressed even more towards ERP in the 1990s (Akkermans et al., 2003; Bahssas, AlBar, and Hoque, 2015; Chen, 2001). ERP is a dynamic and unpredictable exercise that has led to a range of glitches, unfulfilled incentives, budget overruns and less than completely used systems (Alsayat and Alenezi, 2018; Saeed et al., 2017). A dominant aspect of the literature on the topic therefore deals with the problems of success in implementation and other related matters (Alsayat and Alenezi, 2018; Garg and Garg, 2013; Motiei et al., 2015; Narayanamurthy and Gurumurthy, 2017; Saeed et al., 2017; Zerbino et al., 2017). The major advantage expected from any ERP is the lower cost of IT infrastructure and human capital (Gattiker and Goodhue, 2004; Holsapple and Sena, 2005; Madanhire, and Mbohwa, 2016).

The concept of large data also serves to define in real time large and complex, unstructured, semi-structured and structured data, requiring sophisticated management, analysis and processing methods, which offer your insight (Fosso Wamba et al., 2015). Big data has been one of the main technological disruptors since the arrival of the Internet and the digital economy (Agarwal and Dhar, 2014) because of the high data volumes, data diversity, advanced storage, management, analysis and visualization techniques are essential (Chen et al., 2012).

Big data includes high speed data collection and sensor data for real-time analytical data (Chen et al., 2012). Big-data analytics, according to Jeble et al. (2017), consist of a structured method in which market data are obtained and analyzed, mathematical models are designed to describe the (descriptive) phenomenon, a model is built to forecast future outcomes using variable inputs (Predictive Analysis), and a model is designed to optimize or related input variations (Prescriptive Analytics). It uses statistical techniques for the creation of equations, such as simulation, factor analysis, multivariate statistics and mathematical knowledge (Dubey and Gunasekaran, 2015).

The majority of large-scale data investments are not rewarding because most businesses are not ready to make decisions in response to the information derived from data, (Ross, Beath and Qaadgras 2013). McAfee and Brynjolfsson (2012) stress the value of a culture of decision-making based on data, as senior managers take decisions based on data instead of their intuition. Management failure is often listed as a key factor in the performance of Big Data initiatives (LaValle et al., 2014).

The success of large-scale data projects is not only the result of data and analysis, but also includes a wide range of aspects (Garmaki et al., 2016). To solve this problem, the concept of big data analysis has been established (Mikalef et al., 2017). In general, the capacity of big data analytics is defined as a company's ability to provide insights through data management, technology and expertise, which make it competitive (Kiron et al., 2014; Act et al. 2016). The dimensions of big data analytics capability are discussed below:

Gupta and George (2016) conceptualized data as a dimension of big data analytics capabilities. Manyika et al. (2011), expound that in addition to labour, capital, and land, a number of organizations now consider data as a key factor of production. On the contrary, George et al. (2014), recognise five sources of big data as public data; private data; data exhaust; community data; and self-quantification data. Private data refers to firm-owned data that are actively collected by the firms (George et al., 2014; Gupta and George, 2016). Data exhaust refers to the data that do not have a direct value attached to them but can be combined with other sources to yield new insights (George et al., 2014; Gupta and George, 2016). Zhao et al. (2014) broadly classify data into in two types: internal data (data emanating from a firm’s internal operations of an organization); and (ii) external data (data emanating from a firm’s interaction with external actors. In furtherance Gupta and George (2016) make the claim that a firm’s ability to integrate internal and external data creates big data capabilities.

The second dimension of big data analytics capabilities identified by Gupta and George (2016) is technology. Gupta and George (2016) argue that some advance technologies are required to handle the challenges posed by gigantic, diverse, and fast-moving data as occurs in recent times.

3. Resource-Based View

The resource-based view is a theory that has been applied severally by different scholars to explain the mechanism through which organizations attain superior performance and competitive advantage (Dubey et al., 2019; Gupta et al., 2018; Huo et al., 2016; Popli et al., 2017; Yu et al., 2018). From a managerial perspective, the resource-based view emphasizes the managerial efforts aimed at attaining market advantages that are sustainable and allows firms to generate super normal profits (Ali et al., 2016; Anvar, 2017; Bowman and Toms, 2010; Carter et al., 2017). According to Akter et al. (2016) the resource-based view counts on two main assumptions about organizational resources to reveal why some organizations do better than their rivals. First, for every organization in the same industry, the resource possessed by each firm varies (Peteraf and Barney, 2003). Second, the differences in resources held by various organizations are facilitated by the challenge of sharing resources across organizations. In addition to the two assumptions stressed by Atker et al. (2016), a resource-based perspective is emphasized in the **Valuable, Rare, Imperfectly imitable, Organized** context. The VRIO Resource-Based View Theory explains that the success of an organization depends on the degree to which the resources kept by the organization are valuable (V), rare(R), imperfectly imitable(I) resources properly organized(O) (Amit and Schoemaker,1993; Barney et al., 2001). Second, the valuation of resources allows a company to raise net profits and reduce net costs, which in other words, lets businesses capitalize on opportunities and mitigate the hazard (Barney and Arikan, 2001; Barney and Hesterly, 2012). Secondly, the unique aspect means that a few firms will achieve competitive advantages. Thirdly, the imperfectly aspect means, since it is expensive to mimic, that businesses cannot duplicate or substitute such methods directly. Research shows that the complementarity of capital within an organization renders replication impossible for competitors (Morgan et al., 2009). Finally, the

organization, in order to optimize its full competitive efficiency, concentrate on the effective management of essential rare and imperfectly emulated resources (Barney and Clark, 2007).
Again, based on the resource-based view theory, this study proposes that conceptual framework model below:

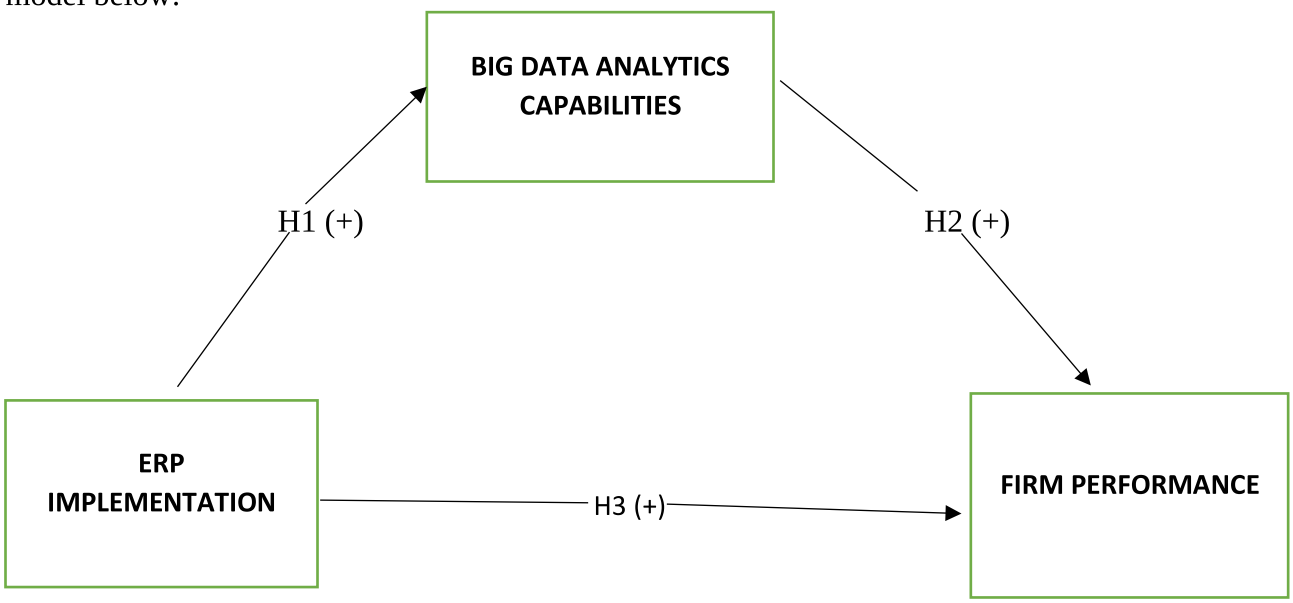

Figure 1: Conceptual framework

3.1 The Relationship between ERP Implementation and Big Data Analytics Capability

Companies are improving their ability to generate competitive advantages by using organizational tools like ERP system to build specific and evolving skills to meet client needs and to adapt to competition challenges (Teece et al., 1997). ERP systems have a huge influence on corporate capability (Masini and van Wassenhove, 2009).
Therefore, this study postulates that:

H1: ERP implementation has a positive relationship with organizational big data analytics capabilities.

3.2 The relationship between Big Data Analytics Capability and Firm Performance

The ability to analyze large data plays a major role, particularly in changing market performance (Akter et al., 2016; Wamba et al., 2017). Some current studies have found that the organizational big data analytics and company results are in a positive relationship (Schroeck et al., 2012; Wamba et al., 2017). In view of this study postulates that:

H2: Big data analytics capability has a positive effect on firm performance.

The relationship between ERP Implementation and Firm Performance

Real-time information and automation enabled by ERP systems helps firms to reduce cost in numerous ways (Ali, van Groenendaal and Weigand, 2020). Some studies looked at the correlation between ERP implementation and corporate performance. Again, a report by Hunton et al. (2003) reaffirmed that the performance of companies adopting ERP was superior to the performance of their peers in the form of investments return, and asset revenue as corporate performance indicators. Accordingly, this study hypothesizes that:

H3: ERP implementation is positively related to organizational performance.

4. Methods and Model Analysis

This research applies the quantitative philosophical assumptions as a mode of analysis of the collected data. Drawing on Leavy (2017), the quantitative approach is mostly used for empirical validation of theories and the determination of the relationship between ERP implementation and BDA capability makes the quantitative technique a most feasible sense. The feasible approach stems from the fact that it involves the use of statistical tools to analyse data for trends, correlations and causal relationships (Cresswell, 2014). The study applied the PLS-SEM technique to analyze the research model the various hypothesized paths. The SmartPLS version 3 was employed (Ringle et al., 2015). When using the PLS-SEM technique, two stages of analysis are required. The first stage involves the test of the measure model and the second stage involves the test of the structural model (Hair et al, 2017).

The primary objective of the study of the metrics model is to determine the reliability and validity of the research model (Hair et al., 2019). The measuring model evaluates the correlation between a latent variable and its indicators. The test of the measuring model ensures that each object tests its variable accordingly. The two key criteria used in testing the measuring model are convergent validity and discriminating validity (Hair et al., 2010; Ramayah et al., 2011). The measurement model assessment began with a test of convergent validity. According to Hair et al. (2017), convergent validity is the extent to which a measure relates to the measures of the same variable. In this study, convergent validity was assessed using the psychometric properties of the variables (Hair et al., 2014). The psychometric properties assessed in this study were Cronbach's alpha, Composite reliability, rho A, and Average variance extracted. This test was necessary to ensure that each of the psychometric properties meets their required threshold (Hair et al., 2019).

The cronbach's alpha, tests the correlation among the indicators of a latent variable, and a benchmark of 0.7 and above is recommended (Chin, 1998; Hair et al., 2010). From Table 1.2, all constructs have Cronbach Alpha values larger than 0.7. Composite reliability on the other hand measures the capacity of the indicators to explain the variance of their latent variable, with a proposed benchmark of higher than 0.7 (Chin, 1998). Again, from Table 1.2, all constructs have composite validities higher than 0.7. Average Variance Extracted (AVE) is the grand mean value of the squared loadings of a set of indicators and is equivalent to the communality of a construct, with a recommended threshold of greater than 0.5 (Hair et al., 2014). All constructions comply with this condition as can be seen in Table 1.2. The Rho_A has recently emerged as an important measure of reliability for PLS-SEM and is currently the only reliable measure of reliability for PLS build scores, with a minimum rho A value of 0.7 suggested by (Dijkstra and Henseler, 2015). Again, all constructs exceeded the recommend threshold as can be seen from Table 1.2.

The study used the online questionnaire which was developed using Google formats and controlled through emails and social media platforms. During the project, 120 respondents received approximately 82 responses. In order to avoid false data, the 82 answers were tested. On the basis of the sampling, 8 answers have been excluded, with 74 analytical replies remaining. Therefore, the study obtained a 61.66 percent response rate. And it is made of 74 reactions obtained.
The demographic characterization of the respondents is provided in this section. SPSS was used to evaluate the demographic profiles of interviewees. Statistical methods were used, including frequency and percentages. Information about the demographic features of the interviewees is shown in detail in Table 1.1 below.

Table 1.1: Demographics

	Responses	Frequency	Percent
State run Enterprise	Yes	16	21.6
	No	58	78.4
How long has your firm been in operation	less than 1 year	5	6.8
	1-2	8	10.8
	2-3	12	16.2
	3-4	8	10.8
	4-5	3	4.1
	5-10	14	18.9
	Above 10	24	32.4
How long have you worked in the company	Less than 1 year	5	6.8
	1 to 3 years	23	31.1
	3 to 5 years	33	44.6
	Above 5 years	13	17.6
Employee Size	Less than 6	18	24.3
	6-29	9	12.2
	30-59	10	13.5
	60-99	10	13.5
	100 +	27	36.5
Ownership of company	Solely Ghanaian Owned	50	67.6
	Foreign Owned	9	12.2
	Joint	15	20.3
Legal form of Entity	Sole Proprietorship	29	39.2
	Partnership	16	21.6
	Limited Liability	16	21.6
	Public Limited Liability	9	12.2
	State owned	4	5.4
	SAP	19	25.7

Which of the following ERPs is used by your organization?	Oracle	10	13.5
	Microsoft Dynamics	43	58.1
	JD Edwards	2	2.7
Education	Undergraduate	38	51.4
	Masters	26	35.1
	PhD	3	4.1
	Certificate/Vocational/Professional	7	9.5
Revenue	< 10,000	16	21.6
	10,0000-30,000	14	18.9
	30,001-100,000	9	12.2
	100,001 –500,000	3	4.1
	500,000 – 1,000,000	8	10.8
	>1,000,000	24	32.4
Company's corresponding industry	Manufacturing	15	20.3
	Financial Services (banking & investments)	6	8.1
	Health	7	9.5
	Retail	12	16.2
	Construction	10	13.5
	Transportation	5	6.8
	Telecommunication	4	5.4
	Electronics and Computing Machinery	6	8.1
	Mining & Minerals	2	2.7
	Agribusiness	7	9.5
	Total	**74**	**100.0**

Table 1.2 Psychometric Properties of the Constructs

Variables		**Cronbach's Alpha**	**rho_A**	**Composite Reliability**	**Average Variance Extracted (AVE)**
Big Data Analytics Capability	Data	0.861	0.863	0.915	0.783
	Data Driven Culture	0.738	0.741	0.835	0.558
	Management	0.921	0.923	0.941	0.761
	Organizational Learning	0.82	0.826	0.882	0.652
	Personnel	0.852	0.856	0.9	0.693
	Basic Resources	0.948	0.95	0.966	0.905
	Technology	0.827	0.838	0.885	0.658
	ERP	0.96	0.965	0.964	0.644
	Firm Performance	0.937	0.941	0.947	0.666

Table 1.3: Item Loading

	BCDA	BCDDC	BCMGT	BCOL	BCPS	BCRES	BCTCH	ERP	FP
BCDA1	0.914								
BCDA2	0.887								
BCDA3	0.853								
BCDDC1		0.762							
BCDDC2		0.701							
BCDDC4		0.794							
BCDDC5		0.728							
BCMGT1			0.894						
BCMGT2			0.876						
BCMGT3			0.902						
BCMGT4			0.864						
BCMGT5			0.825						
BCOL1				0.728					
BCOL2				0.858					
BCOL3				0.873					
BCOL4				0.76					
BCPS1					0.785				
BCPS2					0.862				
BCPS3					0.84				
BCPS4					0.842				
BCRES1						0.954			
BCRES2						0.931			
BCRES3						0.969			
BCTCH1							0.868		
BCTCH2							0.807		
BCTCH3							0.736		
BCTCH4							0.829		
ERP1								0.733	
ERP10								0.898	
ERP11								0.875	
ERP12								0.795	
ERP13								0.874	
ERP14								0.724	
ERP15								0.865	
ERP2								0.802	
ERP4								0.765	
ERP6								0.794	
ERP7								0.801	
ERP8								0.878	
ERP9								0.802	

FPMP1	0.803
FPMP2	0.785
FPMP3	0.849
FPMP4	0.855
FPOP1	0.736
FPOP2	0.8
FPOP3	0.826
FPOP4	0.837
FPOP5	0.845

Discriminant validity

Discriminatory validity guarantees that the concept of construct measures is empirically unique and that other measures in a structural equation model do not capture phenomena of interest (Hair et al., 2010). In this analysis, the discriminatory validity was evaluated using three techniques: The Fornell-Laker criteria, Cross-loading products and Heterotrait-Monotrait correlation ratio (HTMT) The Fornell-Larker criterion suggests that there is discriminatory validity when the square root of the AVE of the factor is greater than its correlation with all other variables in the model (Fornell and Larcker, 1981). In Table 1.4 below the diagonal values in bold indicate the square root of the construct AVE, while the off-diagonal values represent the interrelation between the constructs. Table 4.4 shows that all diagonal variables are greater than off-diagonal values, confirming discriminant validity of the model.

Table 1.4: Fornell-Larker Criterion

	BCDA	**BCDDC**	**BCMGT**	**BCOL**	**BCPS**	**BCRES**	**BCTCH**	**ERP**	**FP**
BCDA	0.885								
BCDDC	0.584	0.747							
BCMGT	0.682	0.437	0.873						
BCOL	0.465	0.556	0.418	0.807					
BCPS	0.685	0.602	0.719	0.561	0.833				
BCRES	0.717	0.505	0.774	0.367	0.715	0.951			
BCTCH	0.729	0.556	0.751	0.422	0.665	0.839	0.811		
ERP	0.622	0.531	0.527	0.27	0.513	0.537	0.565	0.821	
FP	0.742	0.545	0.612	0.523	0.65	0.63	0.708	0.581	0.816

The technique of cross loading suggests that when no research item loads other buildings more than their own, it is discriminating in validity (Hair et al., 2014; Barclay et al., 1995). All items with high cross loads have been dropped according to recommendation (Hair et al., 2012). After all measurements were dropped, the validity of the research model was confirmed in Table 4.5 as all items loaded higher onto their own constructions than on other buildings.

Table 1.5: Cross Loading

	BCDA	BCDDC	BCMGT	BCOL	BCPS	BCRES	BCTCH	ERP	FP
BCDA1	0.914	0.548	0.622	0.45	0.684	0.654	0.632	0.562	0.682
BCDA2	0.887	0.534	0.587	0.469	0.607	0.547	0.615	0.571	0.615
BCDA3	0.853	0.468	0.601	0.313	0.523	0.701	0.691	0.541	0.673
BCDDC1	0.439	0.762	0.301	0.401	0.363	0.28	0.405	0.313	0.429
BCDDC2	0.35	0.701	0.291	0.122	0.32	0.43	0.408	0.432	0.285
BCDDC4	0.535	0.794	0.239	0.494	0.421	0.386	0.416	0.377	0.404
BCDDC5	0.413	0.728	0.448	0.577	0.641	0.409	0.43	0.432	0.482
BCMGT1	0.604	0.456	0.894	0.368	0.702	0.695	0.573	0.451	0.447
BCMGT2	0.549	0.368	0.876	0.373	0.716	0.739	0.615	0.434	0.43
BCMGT3	0.696	0.391	0.902	0.558	0.7	0.662	0.634	0.441	0.561
BCMGT4	0.545	0.322	0.864	0.272	0.494	0.652	0.731	0.495	0.614
BCMGT5	0.573	0.364	0.825	0.229	0.506	0.626	0.736	0.443	0.629
BCOL1	0.305	0.419	0.364	0.728	0.319	0.204	0.325	0.197	0.432
BCOL2	0.39	0.528	0.383	0.858	0.454	0.312	0.431	0.38	0.55
BCOL3	0.347	0.356	0.282	0.873	0.435	0.236	0.246	0.136	0.331
BCOL4	0.438	0.466	0.312	0.76	0.574	0.402	0.337	0.168	0.355
BCPS1	0.553	0.528	0.521	0.455	0.785	0.591	0.582	0.412	0.491
BCPS2	0.653	0.537	0.628	0.407	0.862	0.688	0.685	0.478	0.628
BCPS3	0.535	0.482	0.615	0.493	0.84	0.52	0.423	0.441	0.488
BCPS4	0.531	0.456	0.627	0.522	0.842	0.571	0.508	0.4	0.544
BCRES1	0.697	0.508	0.735	0.336	0.718	0.954	0.828	0.499	0.603
BCRES2	0.628	0.422	0.717	0.307	0.581	0.931	0.78	0.502	0.546
BCRES3	0.717	0.506	0.756	0.4	0.735	0.969	0.786	0.523	0.645
BCTCH1	0.693	0.513	0.642	0.283	0.546	0.777	0.868	0.462	0.693
BCTCH2	0.431	0.421	0.542	0.16	0.436	0.612	0.807	0.493	0.486
BCTCH3	0.586	0.391	0.583	0.396	0.481	0.475	0.736	0.491	0.461
BCTCH4	0.628	0.469	0.655	0.502	0.665	0.811	0.829	0.407	0.624
ERP1	0.428	0.312	0.285	0.203	0.209	0.17	0.192	0.733	0.299
ERP10	0.564	0.512	0.483	0.354	0.472	0.455	0.53	0.898	0.576
ERP11	0.537	0.429	0.557	0.204	0.482	0.556	0.571	0.875	0.564
ERP12	0.42	0.323	0.353	0.111	0.364	0.442	0.466	0.795	0.359
ERP13	0.463	0.42	0.454	0.146	0.418	0.496	0.545	0.874	0.559
ERP14	0.41	0.38	0.468	0.138	0.295	0.454	0.468	0.724	0.409
ERP15	0.5	0.42	0.496	0.117	0.402	0.574	0.559	0.865	0.473
ERP2	0.487	0.502	0.486	0.212	0.422	0.455	0.425	0.802	0.41
ERP4	0.585	0.453	0.304	0.354	0.423	0.304	0.321	0.765	0.419
ERP6	0.585	0.422	0.3	0.449	0.477	0.37	0.423	0.794	0.541
ERP7	0.648	0.516	0.399	0.282	0.447	0.393	0.45	0.801	0.555
ERP8	0.575	0.559	0.524	0.224	0.495	0.481	0.491	0.878	0.502
ERP9	0.381	0.35	0.446	0.031	0.475	0.481	0.47	0.802	0.403

FPMP1	0.497	0.433	0.519	0.503	0.532	0.494	0.553	0.445	0.803
FPMP2	0.607	0.493	0.44	0.345	0.439	0.536	0.51	0.493	0.785
FPMP3	0.705	0.545	0.553	0.349	0.561	0.668	0.689	0.635	0.849
FPMP4	0.581	0.542	0.545	0.332	0.525	0.609	0.703	0.628	0.855
FPOP1	0.546	0.363	0.504	0.431	0.574	0.53	0.469	0.342	0.736
FPOP2	0.605	0.404	0.475	0.48	0.513	0.357	0.488	0.491	0.8
FPOP3	0.638	0.388	0.414	0.535	0.509	0.392	0.538	0.411	0.826
FPOP4	0.594	0.412	0.612	0.487	0.603	0.575	0.669	0.408	0.837
FPOP5	0.674	0.387	0.397	0.413	0.507	0.405	0.521	0.445	0.845

The final test of discriminant validity was the HTMT test. HTMT is the average of the correlations of indicators across constructs measuring different phenomena, relative to the average of the the correlations of indicators within the same construct (Henseler et al, 2015). HTMT test approach indicates that HTMT values must be significantly less than 1, with a value of less than 0.85 ideal (Henseler et al, 2015). Table 1.6 indicates that the highest HTMT value is 0.604, confirming the model possesses adequate discriminant validity.

Table 1.6: Heterotrait-Monotrait Ratio (HTMT)

	BCDA	BCDDC	BCMGT	BCOL	BCPS	BCRES	BCTCH	ERP	FP
BCDA									
BCDDC	0.728								
BCMGT	0.764	0.518							
BCOL	0.546	0.695	0.473						
BCPS	0.795	0.735	0.806	0.665					
BCRES	0.792	0.6	0.828	0.405	0.79				
BCTCH	0.855	0.706	0.86	0.494	0.775	0.932			
ERP	0.68	0.624	0.556	0.309	0.558	0.555	0.632		
FP	0.826	0.638	0.657	0.596	0.722	0.658	0.784	0.593	

5. Structural Model Results

The study's findings were analyzed for the structural model after evaluating the validity and reliability of the model. As a standardized trajectory coefficient PLS provides the scope and significance of hypothesized causal relationship (Hair et al., 2019). In the hypothesized direction of the effect, the parameter estimate of the assumed structural path should be statistically important. If the p value is below the meaning level of 0.05, a direction is considered statistically important. The researchers conducted the bootstrapping study to determine the statistical significance of the loads of the route coefficient (Hair et al., 2014). A Bootstrapping is a technique to resample a large number of subsamples (with replacement) from the original data and to approximate models for each subsample. The researchers thus get a large number of model estimates (typically 5000 or more), which can be used to measure a standard mistake of each parameter of the model. The importance of each parameter can be calculated by means of t-values, based on the standard error (Hair et al., 2014). The path coefficients represent the power of the connections between the buildings, while the t-values calculate the sense of the path coefficient.

Figure 1.2 indicates the path coefficients of the study model, and Figure 4.2 displays t-values. The structural model results are summarized in Table 1.7.

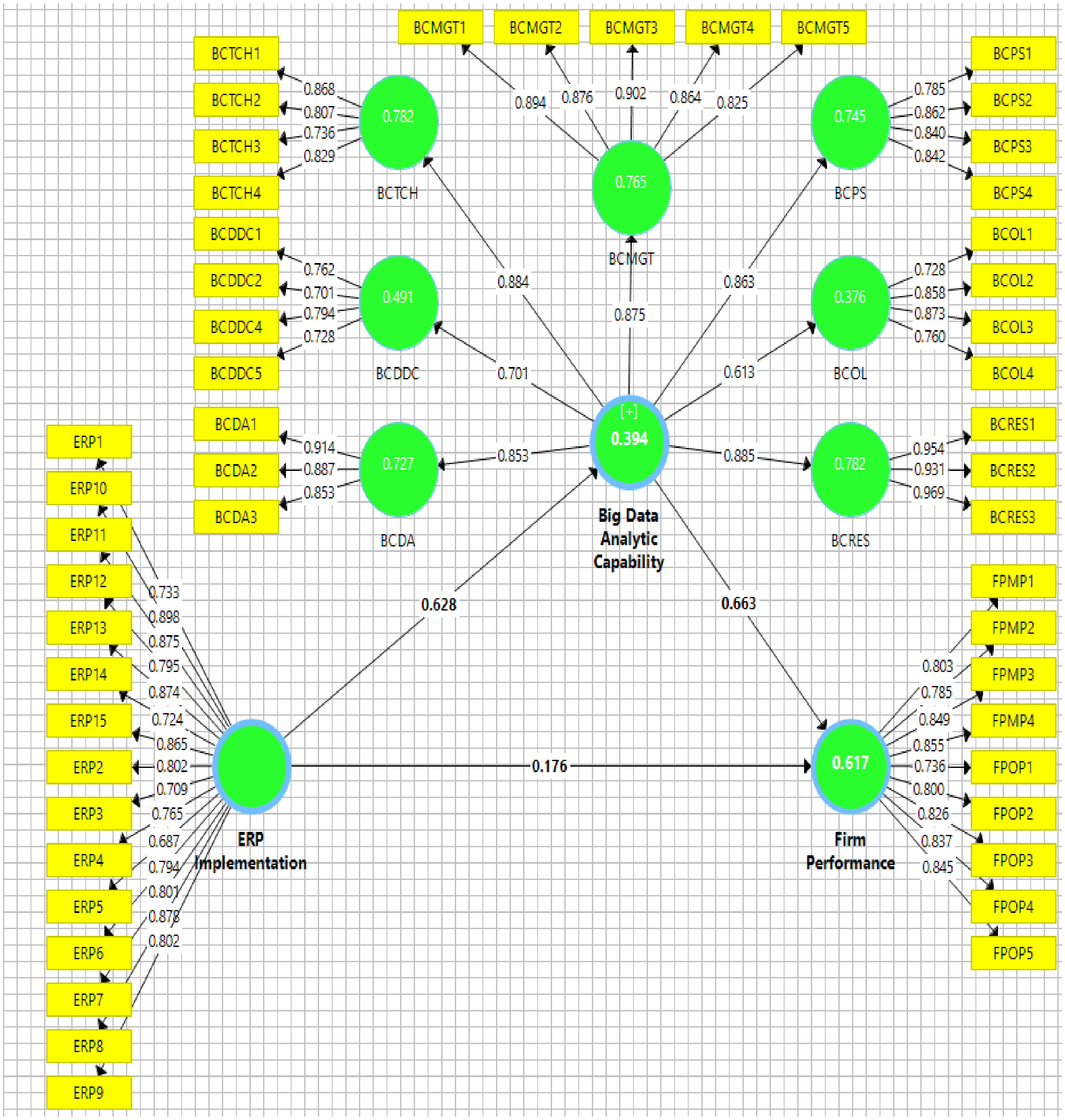

Figure 1.3: Research Model Showing Path Co-Efficient Results

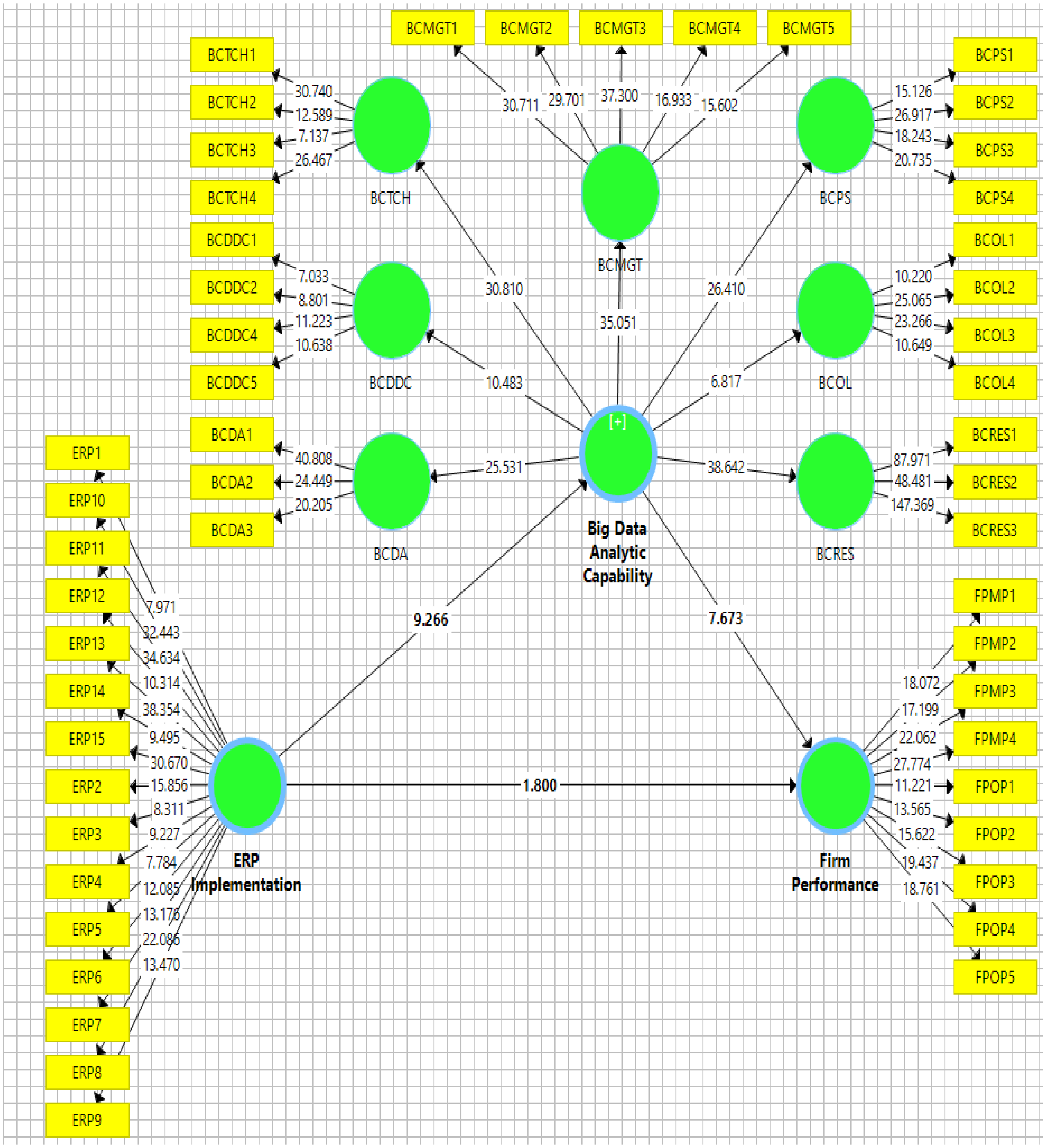

Figure 5.2: Research Model Showing T-values

Hypothesis Testing

The bootstrapping results were used to analyze various hypotheses proposed in by this study. The acceptable standards required for hypothesis testing is through the use of t-values greater than or equal to 1.96 in addition to p-values less than 0.05.

5.1 Hypotheses Testing

Hypotheses		**Original Sample (O)**	**T Statistics (|O/STDEV|)**	**P Values**	**Decision**
H1	ERP -> BDAC	0.628	9.266	0	Supported
H2	ERP -> FP	0.176	1.8	0.072	Not Supported
H3	BDAC -> FP	0.663	7.673	0	
Mediation Test					
H4	ERP -> BDAC -> FP	0.416	5.38	0	Supported

The hypothesis H1 illustrate the direct effect of ERP on big data analytics capability. The results show that ERP has a positive and significant effect on bid data analytics capability with β = 0.628, t-value = 9.266, p-value = 0.

The hypothesis H2 depicts the impact of ERP on firm performance. The results indicate that ERP has a positive but insignificant effect on firm performance (β = 0.176, t-value = 1.8, p-value = 0.72). Thus, the hypothesis was not supported.

Again, the results show that hypothesis 3 which indicates that the effect big data analytics capability on firm performance is supported with a β = 0.628, t-value = 9.266, p-value = 0.

The last hypothesis H4 depicts the mediating role of big data analytics capability on the path from ERP to firm performance. The results show that big data analytics capability positively mediates the relationship between ERP and firm performance with a β = 0.416, t-value = 5.368, p-value = 0. Since the direct effect of ERP to firm performance was not significant, the implication is that big data analytics capability fully mediates the relationship between ERP implementation the firm performance.

6. Discussion of Results

The main objective of this study was to explore the connection between the ERP implementation, the capacity for big data analytics and corporate performance. The study first explores the influence of the ERP execution on the capability of big data analytics. The study finds that the introduction of ERP has a clear and positive effect on the organizational potential of big data analysis. This result supports studies that say that ERP offers broad data analytics capabilities to companies (Shi and Wang, 2018; Sun et al., 2018). Second, the analysis explores the direct impact on company results of implementation of the ERP and Big Data Analytics. The results of the study indicate a favorable but marginal effect on company efficiency on implementation of ERP. Although the research supports existing studies that have shown a positive impact on firm performance of implementation by ERP (Le and Han, 2016, Tarigan et al., 2020), the findings of ERP implementation on corporate performance are somewhat contradicted by the fact that they have a statistically minor effect on corporate performance. On the contrary, the results indicate the strong positive and substantial impact on the organizational efficiency of the broad data analytics capability. This finding confirms the Wamba et al. (2019) report, in which the capacity of organizational big data to achieve enhanced organizational efficiency has been demonstrated. The study also explores the role of mediation in the capacity for big data analytics on the road from ERP towards business efficiency. The results show that the capacity for big data analytics positively affects ERP's relationship with company success. Again, because the direct impact of ERP on the company results was negligible, the result is that the capacity for Big Data Analytics completely mediates the link between ERP's performance. This result provides a justification for studies which have opined for the need for studies to examine the mechanisms through which ERP influences firm performance (Elgohary, 2019; Hassab Elnaby et al., 2012).

The various outcomes of this analysis is examined and the results of the analysis are underlined. It also sets out guidelines, findings, limitations and potential areas for further research.

7. Practical Implication

The study offers some practical implications. In all the study affirms the relevance ERP implementation and big data analytics capability in improving firm performance.

First, the findings of the study disclosed that ERP implementation has a positive and significant influence on organization big data capabilities. This result suggests that when organizations implement ERP, it presents them with several capabilities which includes the ability to handle and process big data to derive useful information for the effective and efficient operations. When adopting ERP, firms must undertake activities such as training employees with requisite and the requisite skills of use ERP, and effective change management to facilitate the and effective and efficient use of the system to reap its benefits (Altamony et al., 2016)

Again, the study finds that big data analytic capability has a positive and significant effect on organizational performance. This result indicates that an organization with high levels of big data analytic capability are more likely to attain high levels of innovativeness. The implication of this result is that organizations seeking to improve upon their performance must endeavor to build capabilities in the area of big data. The implementation of ERP will not only provide big data analytics capabilities but also enhances firm performance.

While the study provides several useful findings, there are some limitations. First, the study was undertaken in Ghana whose prevailing environmental conditions are distinct from other countries. Therefore, the results of this study may not fully apply to firms in countries whose environmental contexts are different from that of Ghana. Therefore, this the study recommends that future works may replicate the conceptual framework in other countries to validate its applicability in different environmental contexts. Again, the study used data obtained from 74 respondents. While this data was adequate to undertake this study (Hair et al., 2019), a higher number of data set would have improved the representativeness of the sample size (Brtnikova et al., 2018). Again, the study recommends that future studies should extend the model with some contextual variables and examine the underlying conditions through which ERP influence form performance.

7.1 Conclusion

This study attempts to study mechanisms that affect the performance of organizations through implementation of ERPs and the Big Data Analytics capability. The study used resource-based view theory as its theoretical underpinning for the development of a research model. The research model conceptualized that the implementation of the ERP has a direct positive impact on the organizational capacity of large data and also on firm performance. The research model for this study was empirically validated with empirical data from 74 respondents. The PLS-SEM analytical technique was used to analyze the research model. The study also found support for three of the four hypotheses formulated further findings of the study revealed that the capabilities of large data analytics mediate the relationship between ERP implementation and performance.

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