Ilkogretim Online - Elementary Education Online, 2020; Vol 19 (Issue 4): pp.4144-4165
http://ilkogretim-online.org
doi: 10.17051/ilkonline.2020.04.764823

Impact of big data predictive analytics of Strategic Alliance in the Big Data Environment: A mediating role of big data culture

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Abstract: Based on the resource-based theory, the current study examines the relationship between big data predictive analytics and strategic alliance performance. Furthermore, big data cultureis treated as a boundary condition between big data predictive analytics and strategic alliance performance. There has been little attention has about big data culture influences on big data predictive analytics and strategic alliance performance, especially in developing countries like Pakistan. A survey instrument was used to record the responses from 331 employees of the national database and registration authority (NADRA) of Pakistan. Study findings show that big data predictive analytics has a positive and significant relationship with strategic alliance performance. It was also found that big data culture plays the role of mediator between big data predictive analytics and strategic alliance performance. The study adds a new perspective and contribution to the literature on big data predictive analytics, strategic alliance performance, and Pakistan's NADRA. Further, the study results explain that big data culture is currently the lifeblood for organizations.With the efficient and effective use of a big data culture environment, companies can boost their standards to compete with other organizations in the market.

KEYWORDS. Big data predictive analytics, big data culture, strategic alliance performance, National database and registration authority (NADRA) sector companies of Pakistan.

I. INTRODUCTION

A strong architecture of information – namely, big data predictive analytics (BDPA) – has created huge interest in the ability to access, analyze and manage huge quantities of data to enhance organizations' performance (Aydiner, Tatoglu, Bayraktar, Zaim, &Delen, 2019; Gupta, Drave, Dwivedi, Baabdullah, &Ismagilova, 2020; Ngo, Hwang, & Zhang, 2020; Saggi& Jain, 2018). Researchers broadly conceptualized in the literature for information systems to process large amounts and varieties of data at speed required to gain relevant insights, thereby enabling companies to gain competitive advantage (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016; Gupta et al., 2020; Pauleen& Wang, 2017; Srinivasan &Swink, 2018).

Even though big data and other factors are greatly studied in recent years, it still needs to be well understood in business and management to leverage the competition globally (Grover, Chiang, Liang, & Zhang, 2018). Strategic management concepts need to be developed and adapted for this new form of business. An area that still needs further development in this aspect is the concept of strategic alliances concerning big data predictive analytics and big data predictive analytics(Akter et al., 2016; Yichuan Wang, Kung, & Byrd, 2018).

Competition needs to be taken care of in a more thoughtful manner by adapting different strategic alliances in the big data environment to improve business and reduce business risk(Fatehi& Choi, 2019). Partner companies (strategic alliances) share their capabilities, resources, and knowledge that connects with their products and services (Chaharbaghi, Adcroft, Willis, Todeva, &Knoke, 2005). They create more comprehensive solutions to specific customer problems and create value through collaborative strategies (Hamilton &Sodeman, 2020; Moeller, Ciuchita, Mahr, Odekerken-Schröder, &Fassnacht, 2013). In this revolutionary era of large data, business processes, partnerships, and strategic alliances, and other types of strategic business solutions have undergone tremendous changes and challenges (Austin, 2010). Recently, the companies announced many large data alliances at the world level (Eriksson, Bigi, &Bonera, 2020; Yufan Wang & Zhang, 2020). Large data promote inter-institutional interaction and creates new trends in collaboration in strategic alliance performance (Raišienė, Bilan, Smalskys, &Gečienė, 2019). It further digs out a specific contend solution that alliance formation in the virtual world seems much easier than before despite the significant increases in the big data environment.

The phenomena of the strategic alliance have not been discussed in the previous researcher's works (Christoffersen, 2013). Different researchers' studies showed that this phenomenon needs attention to explain the organization's success (Gomes, Barnes, & Mahmood, 2016). There is a need to revisit traditional ideas in this area to ensure that they are still relevant and compatible with new business processes in the internet age (Darvazeh, Vanani, &Musolu, 2020; Pigni, Piccoli, & Watson, 2016). A better understanding of alliances in strengthening the economy will reduce the likelihood of the coalition failing(Gomes et al., 2016). According to Kim (2013), data control is a priority for companies that want to grow and stay competitive. It gets a competitive advantage by using the data for all stakeholders' benefits and improve companies' growth (Johnsen, Miemczyk, & Howard, 2017; Saeidi, Sofian, Saeidi, Saeidi, &Saaeidi, 2015).

The existing literature on big data culture shows that it shapes big data predictive analytics and strategic alliances(Dubey, Gunasekaran, Childe, Blome, & Papadopoulos, 2019). This strategy helps the organization and its allies compete in the business market (Dyer, Kale, & Singh, 2001). The Previous researcher only links big data culture with performance management(Pugna, Duțescu, & Stănilă, 2019), institutional environment (Dubey et al., 2019), and decision making (Frisk & Bannister, 2017). Still, a mediating role of the BDC relationship between thebig data predictive analytics and strategic alliances performance did not give much attention to scholars in the past. The current study fills the literature gap and investigates the relationship between big data predictive analytics, big data culture, and strategic alliance performance.

In Pakistan, companies do not significantly take advantage of big data (Ahmad, JianMing, & Rafi, 2019; Iqbal et al., 2018; Yasmin, Tatoglu, Kilic, Zaim, &Delen, 2020). Based on the previous studies' and above arguments, there is still a need to know how big data culture can align with strategic alliances for getting market success with the support of big data predictive?. Several studies show that big data predictive has importance for the alliances for getting competitive advantage (Lee, 2019; O'Dwyer& Gilmore, 2018). Thus big data predictive analytics is an important factor that can enhance the relationship of the big data culture and strategic alliance performance (Akter et al., 2016; Dubey et al., 2018). We can assume that BDC will have a mediating role between BDPA and SAP (Figure 1 showing the study proposed model).

Based on the above arguments we can develop the following research questions of this study.

RQ1. Doesbig data culture influence the performance of strategic alliances?

RQ2. Do big data culturehas a role in strengthening the relationship between big data predictive analytics and strategic alliance performance**?**

Furthermore, the current study's research design framework main contribution in the literature of strategic alliance performance. Firstly, it investigates the relationship between big data culture analytics and strategic alliance performance. Secondly, it will explore the mediating effect of big data culture between big data predictive analytics and strategic alliance performance.

II. THEORETICAL FRAMEWORK AND HYPOTHESIS DEVELOPMENT

Organizational learning theory views learning capacity as one of the main factors influencing a company's international competitiveness. According to (Lakpetch&Lorsuwannarat, 2012), the proportion and relative importance of knowledge-based industries are increasing day by day. So, learning organization has importance in a strategic alliance. Further, the resource-based theory that entrepreneurial resources have recently emerged as an alternative way of understanding industrial organizations and their big data culture. Trust is also a role in strategic management, so the trust-based theory is important for the organization's strategic alliance (Das &Teng, 2000).

2.1 The Strategic Alliance Performance Concept

A strategic alliance has attention from practitioners and scholars in past studies. It has importance for achieving the strategic goals for the organization. A strategic alliance is a strategic goal of strengthening or developing a competitive advantage by two or more companies (or specific business or occupational departments) with common strategic interests, developing or own markets, and jointly using resources through various agreements (Prashant &Harbir, 2009). A cooperative mode in which the contract's advantages are complementary, or the advantages are dominant; the risk is shared. The level of production factors is two-way or multi-directional. As an innovation of the modern companies' organization system, the strategic alliance has become an important means for companies to strengthen their competitive advantage(Lenssen, Blagov, Bevan, Cui, & Jiao, 2011). Since alliance performance mostly involves the completion of goals, we can identify three levels of performance related to alliance goals: 1.financial performance, 2. operational performance, 3. organizational effectiveness. All these three levels of performance, organizational effectiveness is the most important(Musarra, Katsikeas, & Robson, 2016; Wu, Wang, & Chen, 2017).

A strategic alliance is the most important element for the complex process when two different organizations set attributes of culture, norms, and other competencies (Lioukas, Reuer, &Zollo, 2016). The necessary peculiarities for any organization are beneficial to filling a lacuna in the market that an organization faces. Based on the past research, it is noted that the following are the key strategic alliance characteristics in big data that are necessary for the organizations in any sort of business. There is always a strategy; a strategic alliance is also developing based on these strategies, organization goals, and objectives to achieve the organization's goals and objectives (Christoffersen, 2013).

In this digital era, the alliance has significance, especially for companies around the globe. So, the measurement of alliance performance is an essential issue in strategic management, and it is also multi-dimensional, complex, and lacks clarification. Empirical research on early alliance performance relies heavily on various financial and objective indicators (revenue, persistence, etc.) to measure alliance performance (Golesorkhi, Mersland, Randøy, &Shenkar, 2019; Wassmer, Li, &Madhok, 2017). Objectivity indicators are often not always the most important outcome of strategic alliances. For example, for a transnational strategic alliance, the goal may not be financial profitability, but rather to use the alliance form to achieve certain motives, such as improving the parent company's knowledge, improving the parent company's strategic position, and gaining legitimacy(Jiang, Li, & Gao, 2008; López-Duarte, González-Loureiro, Vidal-Suárez, & González-Díaz, 2016). Therefore, the degree of achievement of a transnational strategic alliance's objectives may not be fully reflected by objective indicators such as finance. It means that both objective and subjective have the importance of strategic alliance performance. Therefore, we believe that when accurate, objective indicators are not available, supplemented by subjective indicators, we can better measure alliance performance (Kobarg, Stumpf-Wollersheim, &Welpe, 2019).

2.2. Big data Predictive Analytics and Strategic Alliances Performance

The use of new technological capabilities, which opens big data facilities for business people and other stakeholders. It helps corporations to become more customer-oriented. Against the backdrop of competition with social networks, traditional media are forced to rebuild, lose an audience, and be loyal to them for years. Big data analysis provides accurate information about users. According to the international consulting company BCG, the more accurate information, the more media corporations can earn. The example in the below table shows this dependence clearly. Big data is a huge amount of information of different types: images, video, text, geodata, weblogs, and machine code. All information is in different repositories and is difficult to analyze using traditional methods. For this purpose, specialized technologies are used, including artificial intelligence and machine learning (Provost & Fawcett, 2013).

However, as we have pointed out on several occasions, the evolution of Big data today requires overcoming the current state of isolation, zeal, and atomization, and betting on intercorporate collaboration to face the new challenges that the future poses to the management of data ((H. Chen, Chiang, &Storey, 2012; Phillips-Wren, Iyer, Kulkarni, &Ariyachandra, 2015). It is estimated that in the next two years, the business volume associated with Big data, analysis, and data management solutions will multiply by 6. It is increasing at a sustained rate of more than 25% and surpassing 40 billion Dollars (Dubey et al., 2019; Dubey et al., 2018). A source of business opportunities that have led to large companies' first strategy moves a path that will soon be followed by smaller organizations.

A path aims to lead the greater use of Big data and the huge amount of data that not only accumulates today incorporate databases, but is estimated to grow exponentially over the next five years and that requires, for this, the establishment of contacts, pacts, and alliances between companies that offer complementary products and services (Akter et al., 2016).

Big data and the digital market present, for some time now, strategic alliances that have undoubtedly become vital for the future (Akter&Wamba, 2016). Some of the sectors are currently more affected by customers' demands and the need to have elements that allow companies to significantly outperform increasingly competition (Eggert, Thiesbrummel, &Deutscher, 2015). These issues are especially relevant in different mobile companies limited to a terrain increasingly open and subscribed to competitiveness. It is already very high today but still with a significant operating margin to host recent creation companies. In the current era, the digital market is highly competitive but still offers interesting opportunities. For all this, it is easy to understand why the digital sector has been betting clearly and seamlessly for a few years now, for big data and the benefit. That data analysis brings to its business model; operations are undoubtedly intimately linked to data treatment and obtaining sensitive information through them (Marshall, Mueck, & Shockley, 2015). In all its dimensions, the importance of big data for companies in the digital sector is necessary to talk about the types of data that are most sensitive for these organizations, which, as we will see, have very specific characteristics.

Big data predictive analytics has importance for the organization's performance. Further, it improves the alliance's performance in any era. It means that big data is important both for the organization and for the long-term strategic alliance performance.

Based on the above arguments, the following hypothesis is proposed the following hypothesis;

H 1: Big data predictive analytics influence the strategic alliance performance of an organization.

2.3. Big Data Culture and Strategic Alliance Performance

According to Bail (2014)study, big data culture has a primary function in companies' strategic performance. Their study results show that big data culture has a positive and significant role in strategic alliance performance. Further, big data culture and company performance have a positive and significant impact on strategic alliance performance(Davenport & Bean, 2018). It means that big data culture is essential for strategic alliance performance(Thirathon, Wieder, Matolcsy, & Ossimitz, 2017). That is the reason that one primary stream investigation in the international strategic alliance field tries to recognize the reasons why one organization establishes linkage with other companies. The motivation presented in different investigations is manifold. The reason is like attaining access to such resources (Das & Teng, 2000; Thirathon et al., 2017). All these previous researcher work explains that big data culture has unique importance for the companiesperformance(Dubey et al., 2019; Frisk & Bannister, 2017). Therefore, big data culture and strategic alliance performance have a link with each other. That shows that big data culture has importance for the strategic alliance in the market.

The literature validates our hypothesis for the target population of the study. So our study assumed the following hypothesis;

H 2: Big data predictive culture has a positive and significant relationship with strategic Alliance Performance.

2.4. Mediating Role of Big data Culture between big data predictive analytics and Strategic Alliance Performance

Many researchers discussed the simple relationship between competitive strategies and big data culture in different firms' structures (Arasa&Gathinji, 2014). Another researcher explained the strategic alliance and competitive performance relationship in the pharmaceutical industry (Bail, 2014; Golesorkhi et al., 2019; Goncalves & da Conceição, 2008). Their findings explain the positive and significant relationship between strategic alliance and competition. Further (Lunnan&Haugland, 2008) explain that of the alliance performance. They indicated that strategic alliance has a vital impact on the organization's performance. Still, in the current competitive environment, the organization has pressure from the external environment. Besides the external environment, their top management needs proactive and pre-disciplinary policies and rules to cope with the current competition and get a good reputation in the market.

Big data culture has an important role in Cartwright's strategic alliance (Achrol, 1991; Cartwright, Cartwright, & Cooper, 1996). Furthermore, Wamba, Akter, Edwards, Chopin, and Gnanzou (2015) explains that big data culture and competitive strategies are also positively and significantly related to each other. It predicts that competitive strategies, bid data culture have the importance of the strategic alliance performance at the company's level (Akter & Wamba, 2016; Kristal, Huang, & Roth, 2010). Furthermore, Hu, Wen, Chua, and Li (2014) study results explain that big data culture and competitive strategies play a role in strengthening the relationship between big data predictive analytics and strategic alliance performance.

The literature validates our hypothesis for the target population of the study, so our study proposed the following hypotheses;Based on the above arguments we proposed our study hypotheses as follows;

H 3: Big data predictive analytics has a positive relationship with big data culture.

H 4: Big data culture positively mediates the relationship between big data predictive analytics and strategic alliance performance.

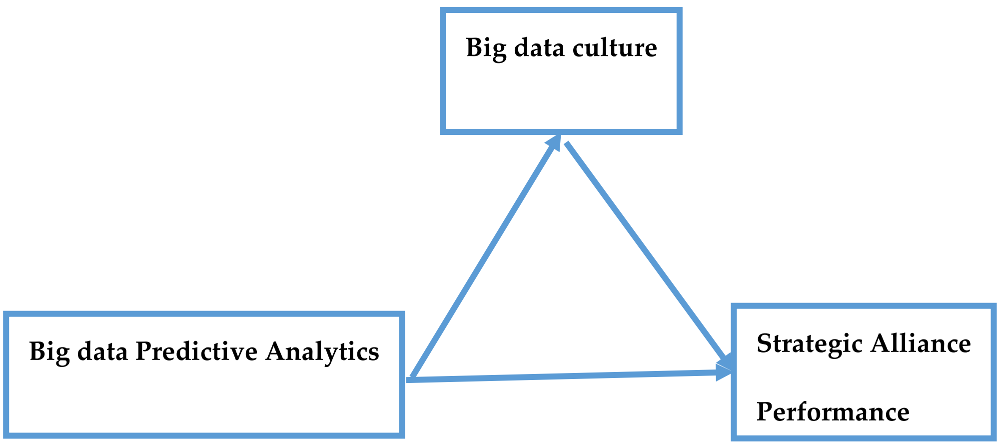

Figure 1. Study Proposed Model

III. RESEARCH METHODOLOGY

3.1 Sampling procedure and Data collection

The present study population is composed of a National database and registration authority (NADRA)working in Pakistan. NADRA has a vital role in big data analysis in the country. In this study, data were collected from employees of the authority.A total of 420 questionnaires were distributed among the participant. We get back 331 useable responses.

3.2 Common Method variance bias Test

In the study data collected from one source. Therefore, it is a common perception that common bias will exist (Podsakoff, MacKenzie, Lee, &Podsakoff, 2003). Data variance if increases than 50% then there will be a CMV problem (Harman, 1976). The result extricated that all the items in the model were categorized into three constructs. All the construct variance was less than 35% which is lower than 50% (Hair Jr, Matthews, Matthews, &Sarstedt, 2017). Which is acceptable for further data processing.

3.3 Measurement Scale

After we matched key respondents and deleted missing data, the final sample included 331 partner companies (486 respondents). Inter-rater reliability was checked to find that the two respondents share similar views about key alliance characteristics such as alliance age and alliance scope. The main variables were measured with multi-items rated on a seven-point scale, from 1 (strongly agree) to 5 (strongly disagree). In this study, all the questionnaires were adapted from the previous researcher's studies.

Strategic Alliance Performance. Six items scale was used to measure the strategic alliance performance scale was adapted from (Ariño, 2003; Zhou et al., 2016) study. 13 items were part of these variables, but only six items were adopted, which were relevant, and their factor loading was higher than .50. Its Cronbach's alpha was .86.

Big data Predictive analytics. The scale for the big data predictive analytics was adapted from study. Only eight items were utilized, and its Cronbach's α .88.

Big data culture. The big data culture scale was adapted from the previous work of (Caprara, Barbaranelli, Bermudez, Maslach, & Ruch, 2000). Big data culture was gauged with nine items—Cronbach's α .86.

Control Variables. In this study, five demographic factors were included, i.e., Age, gender, partner company name, experience, and qualification.

3.4. Descriptive Analysis

The response rate was about 67% that satisfied the minimum criteria to obtain data for the pilot study (Aminu&Shariff, 2015). Each variable's reliability was checked; the value of Cronbach alpha (α=.72) is satisfactory according to the threshold values standard ((Christmann&Van Aelst, 2006). In the data feeding process inclusion and exclusion, the process was also carried out; only filled questionnaires were included, and other incomplete questionnaires were discarded.

Above table 1 shows the data's reliability, which explains that overall, all the variable's reliability is greater than Cronbach's threshold value (α). So, the variables satisfied the need for reliability.

3.5 Assessment of Model Fitness

Model fitness is the last step before performing other statistical techniques such as correlation and regression to reject or accept the proposed hypothesis model to examine data's fitness. The following criteria are mentioned in the literature (Reilly & Doran, 1996; Roh, Ahn, & Han, 2005) to the company whether the proposed model is fit or not:

In Table 1 one factor model analysis the values of $\chi 2/df$ is 2424.53 and CFI=0.93, NFI= 0.88, GFI=0.92, and RMSEA=0. 0.76, which is showing a strong model. Moreover, the results explain that the model is statistically significant overall. All the values are around threshold values of $\chi 2/df$, CFI, NFI, GFI, and RMSEA.

Table 1 shows that all fitness index values had achieved the required level except for Parsimonious fit. Therefore, the model is good enough for the analysis.

Table 1. Model Fit Summary

Name of Category	Name of Index	Index Value	Required Level
Absolute Fit	RMSEA	.076	**< 0.08**
	GFI	.92	>0.90
Incremental Fit	CFI	.93	>0.90
Normal Fit Index	NFI	.88	>0.90
Parsimonious Fit	Chi-Square	2424.53	<5.0

3.5 Descriptive Statistics

In this study, responses were recorded from both males and females. In the current research work, the ratio of males is higher than females. Table 2 results explain that explains overall 210 males respondents and 121 females respondents in the study gave their valuable feedback. In this study, 67% of males and 36.5% of females respond to this study.

Table 2 shows that the highest response rate remained between 31 years of age to 35 years of age. The minimum response was recorded between the age of 41 and above. So, it means that in this study, most of the participants were matured and had work experience in NADRA. Table 2 results elaborated on the education level of the participants. Most of the respondents were master's degrees 166 (50%), 107 (32%) M.Phil./MS, 7 (2.1%), and 51 (15.4%) were bachelor degree. It means that the lowest rate of responses comes from Ph.D./others participants and higher responses recorded from master's degree holders.

Table 2 explains that 17 respondents were 1-5 years of experience, 158 were 6 to 10 years of experience, 90 were 10 to 15 years of experience, 55 were 16 to 20 years of experience, and 11 were 21 years of experience. Maximum respondents have experienced between 21 and above years experience participants.

Table 2 depicts overall, 8 CEO, 75 directors, 93 HR managers, and 100 marketing and 55 finance managers gave their feedback for the current study. Overall, the marketing manager's response rate was higher than the other respondents.

Table 2 clearly shows the respondents from Punjab (41%), Sindh (31%), Baluchistan (6.6%), Khyber PukhtoonKhwa (13%), and 8.5% from Kashmir and Gilgit Baltistan recorded their responses, respectively. Maximum responses received from Punjab and minimum from Baluchistan.

Table 2. Descriptive Statistics

Sample Information	Types		No. of Samples	%age
Gender	Male		210	66
	Female		121	36
Age	20-25years		61	18.4
	26-30 years		117	35.3
	31-35 years		102	30.8
	36-40 years		27	8.2
	41 and above years		24	7.3
Designation	CEO		8	2.4
	Director		75	22.7
	HR manager		93	28.1
	Marketing Manager		100	30.2
	Finance Manager		55	16.6
Education	BA		51	15.4
	Master		166	50.2
	M.Phil/MS		107	32.3
	Ph.D/other		7	2.1
Working Experience	1-5 years		17	5.1
	6-10 years		158	47.7
	11-15 years		90	27.2

	16-20 years		55	16.6
	21 and above years		11	3.3
Provinces	Sindh		102	30.8
	Punjab		136	41.1
	Baluchistan		22	6.6
	Khyber Pakhtunkhwa		43	13.0
	Kashmir/Gilgit Baltistan		28	8.5

IV. RESULTS

In the present study, the following statistical software and tools were employed to interpret the research questions' results and test the proposed hypotheses.

Through factors analysis, we can analyze data factors like KMO values, Pattern Matrix, and further reliability of items that can also be concluded.

The table illustrates that the KMO value is 0.956 and thus, explains that factor analysis can be carried out for underlying structure detection of all the variables. The statistically significant $\chi2(df.=465, N=245) = 11916.269$, $p< .001$ suggests the appropriateness of using factor analysis. All these factors factor loading is above .60, and reliability values are also satisfactory, according to threshold values >.70). All variables above .60 were included in the table, and those who had values less than .60 were excluded from the list.

As shown in Table 3, all variables items, factor loading, Cronbach's alpha, composite reliability, and average variance extracted (AVE) were greater than 0.80 for all constructs. As a result, Cronbach's alpha and CR suggested that the scales were relatively stable and that all of the latent constructs values surpassed the 0.70 minimum threshold mark. The Average Variance Extracted (AVE) of each latent construct was determined [.70] to ensure the variables' convergent validity. In the model, the latent constructs can account for the lowest half of the observed variable variance. As a result, the AVE for all constructs should be greater than 0.5. Table 4 reveals that all of the AVEs are greater than 0.5. As a result, the study model's convergent validity was verified. The measurement model's convergent validity and internal consistency were verified by these findings.

Table 3 illustrated that the inter-correlations of the build of all other observed variables in the model are greater than the cross-loading of all observed variables. As a result, these results validated the cross-loading evaluation criteria and offered appropriate evidence for the discriminant validity of the measurement model. As a result, the proposed conceptual model was expected to be satisfactory, with sufficient reliability, convergent validity, and discriminant validity verified, as well as research model verification.

Table 3. Construct Reliability and Validity

	Indicator	Factor Loading	Cronbach's Alpha	rho_A	CR	Average Variance Extracted (AVE)
Big Data Predictive Analytics	BDPA1 BDPA2 BDPA3 BDPA4 BDPA5 BDPA6 BDPA7 BDPA8	. .811 .838 .871 .874 .830 .882 .865 .926	0.951	.958	.959	0.745
Big data culture	BDC1 BDC2 BDC3 BDC 5 BDC 6 BDC 7 BDC 8	.859 .850 .873 .902 .862 .806 .914 .923	0.956	0.959	0.963	0.764
Strategic Alliance Performance	SAP1 SAP2 SAP3 SAP4 SAP5 SAP6	.944 .826 .967 .970 .960 .902	0.968	0.970	0.964	0.864

Table 4 depicted the model's Fornell and Larcker criterion evaluation, in which the squared correlations were compared to correlations from other latent constructs(Ab Hamid, Sami, &Sidek, 2017). Table 4 shows that all of the correlations were smaller when compared to the squared root of average variance exerted along the diagonals, meaning that the discriminant validity was satisfactory. This demonstrated that the observed variables of each construct indicated the assigned latent variable, confirming the model's discriminant validity. The inter-correlation among the variables explains a strong relationship between the variables; if the relationship and the variables are higher and significant. It explains the relatively same content. On the other hand, if the two factors' inter-correlation is low, it explains two different content (G. Chen et al., 2016).

Table 4:Fornell-Larcker Criterion

	BDC	BDPA	SAP
BDC	0.874		
BDPA	0.385	0.863	
SAP	0.794	0.486	0.929

Furthermore, observing the direct and positive influence of the big data predictive analytics on strategic alliance performance (H2), the findings from Table 6 and Figure 2 endorsed that the big data predictive analytics positively influenced strategic alliance performance ($\beta = 0.174$, $T = 3.839$, $p < 0.05$), and confirmed H1.

The effect of big data culture on strategic alliance performance was significant ($\beta = 0.389$, $T = 7.026$, $p < 0.05$), therefore supporting H2. Furthermore, ($\beta = 0.209$, $T = 3.829$, $p < 0.05$), therefore supporting H3.

Table 6:Path Coefficients and T-Statistics

Hypothesis	Coefficient	T Statistics (|O/STDEV|)	P Values	Decision
BDPA -> SAP	0.741	0.046	15.944	Supported
DPA -> BDC	0.398	0.057	7.026	Supported
BDC -> SAP	0.209	0.055	3.829	Supported

4.1 Mediation analysis

Table 7 explains the direct relationship of the BDC with strategic alliance performance shows that big data predictive analytics play the role of moderator between big data culture and strategic alliance performance. So, our hypothesis H3 is proved. Further, Table 7 and figure 2demonstrating the mediatingeffect of the big data culture between the big data predictive analytics and strategic alliance performance.

Table 7: Total Effect

Direct Path	Coefficient	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
BDPA -> SAP	0.504	0.061	8.252	0.000
BDPA -> BDC	0.398	0.057	7.026	0.000
BDC-> SAP	0.741	0.046	15.944	0.000

Table 8 shows that there is a positive and significant relationship between the bid data predictive analytics and strategic alliance performance. Further, table 8 findings, (β = 0.295, T = 6.489, $p < 0.05$) show that bid data culture strengthens the relationship of the big data predictive analytics and strategic alliance performance. Based on these results our H4 is approved.

Table 8. Specific Indirect Effect

	Coefficient	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
BDPA -> BDC -> SAP	0.295	0.045	6.489	0.000

Figure 2 demonstrated that factor loading and t values of the variables big data culture big data predictive analytics and strategic alliance performance.

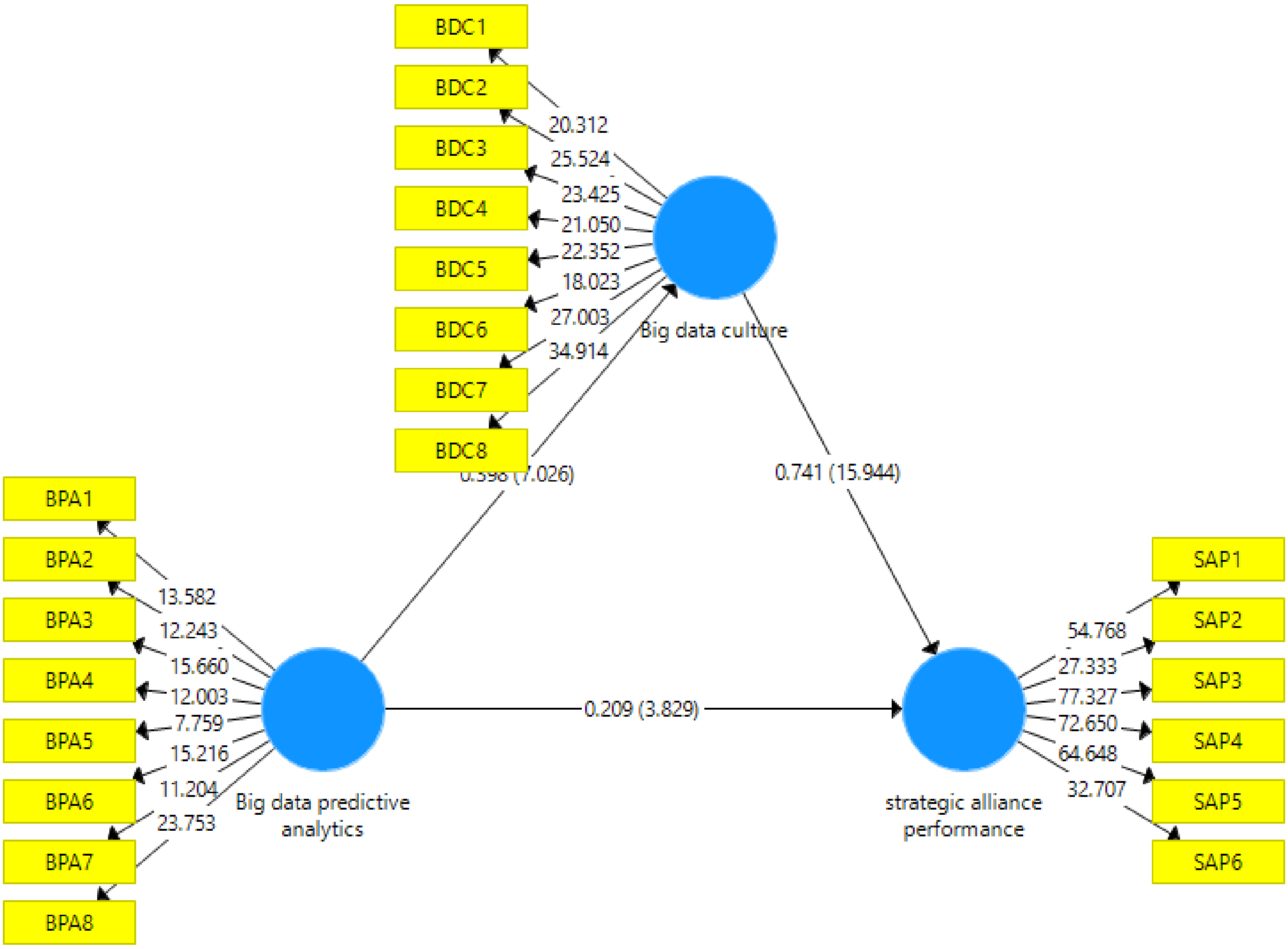

Figure 2. Big data culture Showing mediating among study Variables

V. Discussion

The study's objective was to know the importance of big data analytics with strategic alliance performance. This study untapped the relationship between big data predictive analytics, big data culture. Firstly study shows that big data predictive analytics has a positive and significant relationship with strategic alliance performance (Akter et al., 2016; Chehri, Fofana, & Yang, 2021; Yufan Wang & Zhang, 2020).

Similarly, big data cultureis the main source of strategic alliances in the big data environment for achieving effective marketing intelligence (Akter et al., 2016; Gunasekaran, Lai, & Cheng, 2008).

According to the study's findings, before establishing a partnership to gain a competitive advantage from big data, any company that enters a strategic alliance must explore and analyze each other's different attributes (Lunnan&Haugland, 2008). Here, organizations can consider companies' experience in certain activities that can lead to mutual help and help each other improve the future. Given the importance of resource-based theory, to build strategic alliances in a big data environment, a good reputation should be seen as a valuable asset that helps the company better access scarce resources from the outside (L. H. Chen, Cheyer, Guzzoni, & Gruber, 2014; Gillis, Combs, &Ketchen Jr, 2014)

This research also suggests that it is essential to be successful in a large data environment partnership to highlight complementary skills, resources, and expertise. This will bring you more learning opportunities. Besides, the combination of additional resources can play a vital role in enhancing the competitive advantage of the alliance, thereby enabling the alliance to succeed (Ferreira, Coelho, &Moutinho, 2020; Grigoriou&Rothaermel, 2017; Ireland, Hitt, &Vaidyanath, 2002).

5.1. Theoretical Contributions

The study's main contribution was to understand better strategic alliances' structure between data analytics business companies and their supporting procedures. It is noticed that there is a need for norms and processes, which worked in the past to be re-examined under the new, rapidly changing electronically boosted business environment. As an essential part of business strategies, this research focuses on strategic alliances between companies to perform data analytics business activities and create a better foundation for analyzing partnership formation between big data companies and their success factors and dimensions. It has been found that in the modern, rapidly evolving electronically boosted market world, norms and processes that operated in the past must be re-examined. This research focuses on strategic partnerships between companies to conduct data analytics business activities and provide a stronger foundation for evaluating relationship creation between big data companies and their success factors and dimensions as an important part of business strategies. This study is extended the previous researchers' work, who indicated the numerous factors of big data predictive analytics with a company's performance except for strategic alliance performance (Srinivasan &Swink, 2018). Thus, this research contributes to the literature on big data predictive analytics and strategic alliance performance. Previous researchers only link big data predictive analytics with supply chain management (Darvazeh et al., 2020; Ferraris, Mazzoleni, Devalle, & Couturier, 2019), company performance (Akter et al., 2016), and change management (Darvazeh et al., 2020). The current study extended the work by adding a moderator big data culture between big data predictive analytics and strategic alliance performance.

5.2. Practical Contribution

Study findings explained and opened new directions for the strategic alliance performance in big data environment and suggested the following main things: (a) big data analytics and strategic alliance performance provide a direction for the practitioners to practice the importance of big data analytics with the strategic alliance performance in their companies, which shows a strong association in the current study. (b) Companies' employees truly understand the importance of big data predictive analytics with strategic alliance performance. (c) Before spending resources on the different other projects, companies need to think about the big data's practicability for successful operations individually and with their allies.

The study's main contribution, which we got from the survey, is that big data is an important tool for companies' success. This factor companies must be considered for their survival and coordination with their allies.

Elemental categorization is needed for theoretical development in any field of knowledge because it provides a better perspective for researchers. Therefore, this research contributes to the body of knowledge in their respective fields by providing fundamental classifications.

The practitioners' implications for the future will remain supportive of investigating the importance of big data analytics and its importance for the long run's strategic alliance. Further, this study result is most important for the other organization to analyze the importance of big data significance for its SWOT analysis. Furthermore, the results can be applied to the different IT and other organizations that know the importance of big data importance and strategic alliance performance in the end. This research gives a future avenue for the organization to work according to the need of the day.

5.3. Limitation and Future Research Direction

There were some strengths and limitations associated with this study. Firstly, this study contributes to the literature on strategic alliance performance. But, it still has some limitations which provide directions for future research. This study only limited big data predictive analytics and strategic alliance performance with a mediating effect of big data culture; big data culture can be used as a moderator. Second, this study is limited to the cross-sectional approach; a longitudinal approach can be used for in-depth analysis in future research. This study is only limited to the developing country context; a comparative study can be conducted in future concern. In this study, a survey method was used to collect the data from the participants. In future research, a multi-method approach can be used for the data collection. This study is only limited to Pakistan's NADRA; in future research, it is suggested to collect the data from others like in the health sector, immigration, multi-cellular companies, education, or any other business organization.

VI. CONCLUSION

The study's main objective was to investigate the relationship between big data predictive analytics, big data culture, and strategic alliance performance. In this regard, the study formulated four hypotheses to explain the role of big data predictive analytics, big data culture, and strategic alliance performance. Most of the participants have the view that strategic alliance has importance for the organization's performance. First, there appears a positive direct association between big data predictive analytics and strategic alliance performance in the current study. Secondly, there is also a significant and positive direct relationship between big data predictive analytics and big data culture. Thirdly, the study also empirically found a positive and significant impact of competitive strategy on strategic alliance performance. Finally, it was found that big data culture has a mediating role between big data predictive analytics and strategic alliance performance. Study findings indicated that big data culture strengthens the relationship of big data predictive analytics with strategic alliance performance.

Strategic Alliance Performance (Ariño, 2003; Zhou et al., 2016)

1. Strategic Alliance is more important for the Economic Performance of the company.
2. Strategic Alliance is important for introducing new products or services into the market faster than our competitors
3. Our success rate of new products or services has been higher than our competitor
4. Our productivity has exceeded that of our competitors

5. Strategic Alliance able to search for new and relevant knowledge
6. Strategic Alliance able to build a trust climate among the partners

Bid Data Predictive Analytics (Mello & Martins, 2019; Ren, Fosso Wamba, Akter, Dubey, & Childe, 2017)

1. The infrastructure of the data is sufficient for organizational performance.
2. BDPA helps the organization further polishing Intangible resources.
3. It helps in the promotion of the product and its brand in the market.
4. Big data predictive analytics helps in the development of managerial skills of the partners
5. Big data predictive analytics promote data analytics knowledge practices
6. Big data predictive analytics helps in the development of human skills at the companies' level
7. Big data predictive analytics provides the methodology in tapping intelligence from large data sets
8. Big data predictive analytics predict the future progress of a company

Big data culture (Caprara et al., 2000)

1. We consider data a tangible asset.
2. Big data culture bases our decisions on data rather than on instinct.
3. We are willing to override our intuition when data contradict our viewpoints
4. We continuously assess and improve the business rules in response to insights extracted from data
5. We continuously coach our employees to make decisions based on data
6. We think that BDC helps in the cultural promotion of learning
7. The big decision is made based on a big data culture climate in the organization
8. Big data culture promotes a monitoring system of strategic alliance in the organization

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