

Competitive Approaches of Strategic Alliance in the Big Data Environment, a Moderating Role of Big Data Predictive Analytics in the Case of Telecommunication Sector of Pakistan

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Abstract: Based on the resource-based theory, the current study examines the relationship between competitive strategies and strategic alliance performance of companies. Furthermore, big data predictive analytics is treated as a boundary condition between competitive strategies and strategic alliance performance. Big data of predictive analytics in operations and industrial management has been a focal point in the current era. There has been little attention about big data predictive analytics influences on competitive strategies and strategic alliance performance in literature. A survey instrument was used to record the responses from 331 employees working in telecom sector companies. Study findings show that big competitive strategies have a positive and significant relationship with strategic alliances performance. It was also found that big data predictive analytics plays a role of moderator between competitive strategies and strategic alliance performance. The study adds a new perspective and contribution to the literature on big

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data predictive analytics, strategic alliance performance, and competitive strategy in telecom sector companies. Further, the study results explain that big data analytics is just like the companies' lifeblood in the current era. With efficient and effective use of big data analytics, companies can boost their standards in a competitive environment.

Keywords: Big data predictive analytics, competitive strategies, strategic alliance performance, telecom sector

1. 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 [1-4]. Researchers broadly conceptualized in the literature for information systems to process large amounts and varieties of data at the speed required to gain relevant insights, thereby enabling companies to gain a competitive advantage [1, 5-7].

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 [8]. 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 competitive strategies [5, 9].

Competition needs to be taken care of more thoughtfully by adapting different strategic alliances in the big data environment to improve business and reduce the business risk[10]. Partner companies (strategic alliances) share their capabilities, resources, and knowledge that connects with their products and services [11]. They create more comprehensive solutions to specific customer problems and create value through collaborative strategies [12, 13]. 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 [14]. Recently, the companies announced many large data alliances at the world level [15, 16]. Large data promote inter-institutional interaction and creates new trends in collaboration in strategic alliance performance [17]. 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 strategic alliance have not been discussed in the previous researcher's works [18]. Different researchers' studies showed that this phenomenon needs attention to explain the organization's success [19]. 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 [20, 21]. A better understanding of alliances in strengthening the economy will reduce the likelihood of the coalition failing[19]. According to Kim [22], 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 [23, 24].

According to Porter [25], a competitive strategy is a long-term action plan devised by a company to achieve a competitive advantage over its business competitors. The existing literature on competitive strategies shows that it shapes big data predictive analytics and strategic alliances [26]. This strategy helps the organization and its allies compete in the business market [27]. In the previous studies researchers, only link big data predictive analytics with supply chain management [21], firm performance [5], and change management [21]. Still, a moderating role of BDPA between the relationship of competitive strategies and strategic alliances performance did not give much attention by scholars in past. The current study fills the literature gap and investigates the relationship between big data predictive analytics, competitive strategies, and strategic alliance performance.

In Pakistan, companies do not significantly take advantage of big data [28-30]. Based on the previous studies and above arguments, there is still a need to know how competitive strategies can align with strategic alliances for obtaining market success with the support of big data predictive?. Several studies show that big data predictive has an importance for the alliances for getting competitive advantage [31, 32]. Thus big data predictive analytics is an important factor that can enhance the relationship of the competitive strategies and strategic alliance performance [5, 33]. We can assume that BDPA will have a moderating role between BDPA and SAP (Figure 1 showing the proposed model).

Based on the above arguments, the following research questions have been developed of this study.

RQ1. Do competitive strategies influence the strategic alliances performance of the telecom sector?

RQ2. Does big data predictive analytics affect the strategic alliance performance of the telecom sector?

RQ 3. Do big data predictive analytics play a role in strengthening the relationship between competitive strategies 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 competitive strategies analytics and strategic alliance performance. Secondly, it will explore the moderating effect of big data predictive analytics between competitive processes and strategic alliance performance. These scientific contributions enrich the literature of competitive strategy, big data predictive analytics, and strategic alliance performance. Researchers assumed that this is the first proposed model of the study, which explains the relationship between the independent variable (competitive strategies), big data predictive analytics (moderator), and strategic alliance performance (outcome variable).

The novelty of the study model used in this study has tested for the first time ever and is never being tested anywhere in the world especially in the developing country context and more importantly in the telecom sector. This research also opens new windows for future research to investigate the issue and to add other variables to expand the concept.

2. 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 [34], the proportion and relative importance of knowledge-based industries are increasing day by day. So, learning organization has importance in a strategic alliance. Further, resource-based theory and information process theory that entrepreneurial resources have recently emerged as an alternative way of understanding industrial organizations and their competitive strategies [3, 35]. These two theories are most important for the competitive strategy and big data analytics for the successful strategic alliance performance [36].

2.1 The Strategic Alliance Performance Concept

A strategic alliance has attracted attention from practitioners and scholars in past studies. It has importance for achieving the strategic goals for the organization. A strategic partnership aims to strengthen or develop 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 [37]. 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 [38]. 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. With all these three performance levels, organizational effectiveness is the most important [39, 40]. A strategic alliance is essential for complex processes when two different organizations set attributes of culture, norms, and other competencies [41]. 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 organizations in 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 [18].

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 [39, 40]. 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 [41, 42]. Therefore, the degree of achievement of a transnational strategic alliance's objectives may not be fully reflected by objective indicators such as financial matters. It means that both objective and subjective issues 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 [43].

A strategic alliance allows doing business following governments' requirements to foreign capital and significantly reduces the risks when entering new markets [44, 45]. Companies may conclude agreements on dividing markets into individual spheres of influence or establishing closer cooperation in a particular region [49]. Thus, companies reduce their risks through this strategic technique.

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 for different purposes, like to check company performance etc. According to the international consulting company BCG, the more accurate information, the more media corporations can earn. 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 [45].

In a short time, we have witnessed a profound change in the business landscape of data management. Only two decades ago, the data management in the terms we raised today did not even appear among the corporate priorities. In a few years, the data became much more important and became the value for all companies' survival in the market [93]. It means that both companies' data and their customer's attraction play a significant role.

However, as the research has 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 ([46, 47]. 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 [33, 48]. 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 [5]. Big data and the digital market present, for some time now, strategic alliances that have undoubtedly become vital for the future [49]. 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 [50]. 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 [51]. 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.

H 1. *Big data predictive analytics has a positive relationship with strategic alliance performance of the companies.*

2.3. Competitive Strategies and Strategic Alliance Performance

According to [52] study, competitive strategies have a primary function in companies' strategic performance. The study results in resrecah conducted showed that competitive strategy has a positive and significant role in strategic alliance performance. Further, competitive strategies and company performance have a positive and significant impact on strategic alliance performance[53]. It means that competitive strategy and strategic alliance performance are essential

for getting a competitive advantage in the market [54]. 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 [36]. It means the Competitive strategies have a relationship with strategic alliance performance [55]. Furthermore, [56] explored in their study that strategic alliance performance has importance for the market's performance and security in the current situation to get a competitive advantage. All these factors explain that big data predictive analytics has unique significance for the companies performance [53]. Therefore, competitive strategies and strategic alliance performance have a link with each other.

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

H 2. *There is a positive relationship between competitive strategies and strategic alliance performance for companies.*

2.4. A moderator role of the Big Data predictive analytics between competitive strategies and strategic alliance performance of companies

Many researchers discussed the simple relationship between competitive strategies and company alliance performance [53, 57, 58]. Another researcher explained the strategic alliance and competitive performance relationship in the pharmaceutical industry [59]. Their findings explained the positive and significant relationship between competitive strategies and strategic alliance and performance. Further some other researchers [60] explained that the alliance is an important factor for an organization 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.

Compared to the transactional type relationship or intermitotic relationship, the strategic alliances in nature are long-term enduring, emphasizing its competitive strategies [61]. On the other hand, some investigators claim that even though the strategic alliance is aimed to sustain competitive advantage, in nature. The alliance does not have to be long-term. It will be for a specified period, possibly in the joint product advance team [62]. A strategic alliance has unique importance for the companies for competitive advantages, like a case in which competitors can penetrate or enlarge in an available market [63]. It gets an edge on the other companies.

For companies, big data seek to monitor employees' communication and collaboration activities [68]. This improves the relationship between the company and its employees, partners to be even closer. Channels in which the employees understand their role, within the organization and out of the organization, will be enabled. And the latter will realize the importance of your employees' roles [69]. Further, big data help in the decision-making of any organization [9]. In the current competitive environment, big data, competitive strategies are the most important factors to study the strategic alliance performance of the companies to get a competitive advantage compared to other companies [9, 70, 71]. Further, Ghasemaghaei and Calic [72] explain that big data is important for the organization's competitive strategy and innovation[5, 31, 32]. Based on the above arguments, we proposed our study hypothesis as follows;

H 3. *Competitive strategies positively moderate the relationship between big data predictive analytics and strategic alliance performance of the companies.*

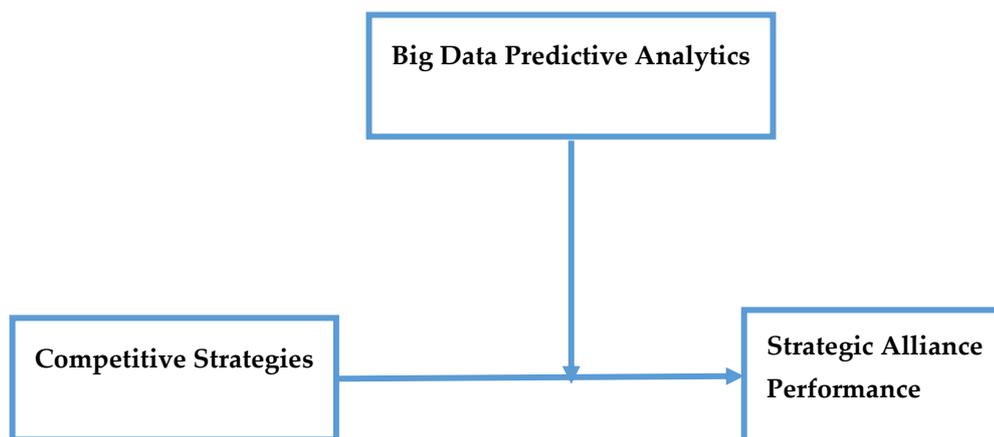


Figure 1. Study Proposed Model

3. Research Methodology

3.1 Sampling procedure and Data collection

The present study population is composed of telecom sector companies working in Pakistan. The details of telecom sector companies were collected from the Pakistan telecommunication authority (PTA) website. Only those telecom companies were selected, which have a strategic alliance with each other. The participants of the companies were Chief executives and top-level managers. Data were collected from the top five telcom companies (Zong, Telenor, Warid, Jazz, and Pakistan Telecommunication Limited (PTCL). These companies were the population of the study. A total of 432

employees of the Zong, Telenor, Warid, Jazz, and Pakistan Telecommunication Limited (PTCL) were selected for the data collection based on a simple random sampling technique. The participant's eligibility criteria were established on behalf of the respondents who know about the strategic alliance in a big data environment. 432 questionnaires were distributed to the participants. Three hundred thirty-one useable responses were received, and they were used for the further analysis process.

3.2 Common Method variance bias Test

In the study data collected from one source. Therefore, it is a common perception that a common bias will exist [64]. Data variance if increases than 50%, then there will be a CMV problem [65]. 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% [66], 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. The six-item scale was used to measure strategic alliance performance scale adapted from [76-78] study. 13 items were part of these variables. Still, only six items were adopted, which were relevant, and their factor loading was higher than 0.50. Its Cronbach's alpha was 0.86.

Big data Predictive analytics. The scale for the big data predictive analytics was adapted from [67, 68] study. Only eight items were utilized, and its Cronbach's α .88.

Competitive Strategies. The competitive strategies scale was adapted from the previous work [69, 70]. Competitive strategies were 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.

3.3. Descriptive Analysis

The response rate was about 67% that satisfied the minimum criteria to obtain data for the pilot study [71]. Each variable's reliability was checked; the value of Cronbach alpha (α =.72) is satisfactory according to the threshold values

standard ([72]. 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.

3.4 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 [73, 74] to the company whether the proposed model is fit or not: In Table 1 one factor model analysis the values of χ^2/df is 2334.52 and CFI=0.91, NFI= 0.89, GFI=0.97, and RMSEA=0. 067, 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 χ^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	.067	< 0.08
	GFI	.97	>0.90
Incremental Fit	CFI	.91	>0.90
Normal Fit Index	NFI	.89	>0.90
Parsimonious Fit	Chi-Square	2334.52	<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 who 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 and 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 telecom sector. 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 PhD/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 of 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 managers response rate was higher than the other respondents. Table 2 clearly shows the respondents from Punjab (41%), Sindh (31%), Baluchistan (6.6%), Khyber Pukhtoon Khwa (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

4. Results

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

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 3, 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 [38,71]. Table 4 reveals that all of the AVEs are greater than 0.5. As a result, the study model's convergent validity was verified. These findings verified the measurement model's convergent validity and internal consistency.

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-loadings 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	.806	0.951	.957	.93	0.744
	BDPA2	.833				
	BDPA3	.873				
	BDPA4	.877				
	BDPA5	.836				
	BDPA6	.881				
	BDPA7	.868				
	BDPA8	.925				
Competitive Strategies	CS1	.867	0.953	0.959	0.960	0.731
	CS2	.842				
	CS3	.862				
	CS4	.898				
	CS5	.865				
	CS6	.820				
	CS7	.905				
	CS8	.916				
	CS9	.698				
Strategic Alliance Performance	SAP1	.944	0.968	0.97	0.89	0.864
	SAP2	.825				
	SAP3	.967				
	SAP4	.970				
	SAP5	.960				
	SAP6	.903				

Table 4 depicted the model's Fornell and Larcker criterion evaluation, in which the squared correlations were compared to correlations from other latent constructs [75]. Table 5 indicates 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 [76].

Table 4. Fornell-Larcker Criterion

	BDC	BDPA	Competitive Strategies	SAP
BDPA	0.535	0.863		
Competitive Strategies	0.696	0.378	0.92	
SAP	0.713	0.484	0.790	0.85

4.1 Regression Analysis

Regression analysis shows how much change brings by independent variables independent variable [77].

Table 5 shows that competitive strategies and big data predictive analytics bring a change of 67% in strategic alliance performance.

Table 5. Regression Analysis Summary

R Square	R Square Adjusted
0.670	0.668

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 competitive strategies on strategic alliance performance was significant ($\beta = 0.699$, $T = 15.724$, $p < 0.05$), therefore supporting H2. Based on the result, we can conclude that all two moderation are significant at t-values >1.96 and p-value <0.05 .

Table 6. Path Coefficients and T-Statistics

Hypothesis	Coefficient	T Statistics (O/STDEV)	P Values	Decision
BDPA -> SAP	0.174	3.839	0.000	Supported
CS -> SAP	0.699	15.724	0.000	Supported
Mod_BDPA_CS_SAP -> SAP	0.092	2.961	0.003	Supported

4.1 Moderation Analysis

Table 7 explains that ($\beta = 0.092$, $T = 2.961$, $p < 0.05$), shows that big data predictive analytics play a role of moderator between competitive strategies and strategic alliance performance. So, our hypothesis H3 is proved. Further, Table 7 and figure 3 show the moderating effect of the big data predictive analytics between competitive strategies and strategic alliance performance. **Table 7.** Total Effect

Direct Path	Coefficient	Standard Deviation (STDEV)	T Statistics (O/STDEV)	P Values
BDPA -> SAP	0.174	0.045	3.839	0.000
CS -> SAP	0.699	0.044	15.724	0.000
Mod_BDPA_CS_SAP -> SAP	0.092	0.031	2.961	0.003

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

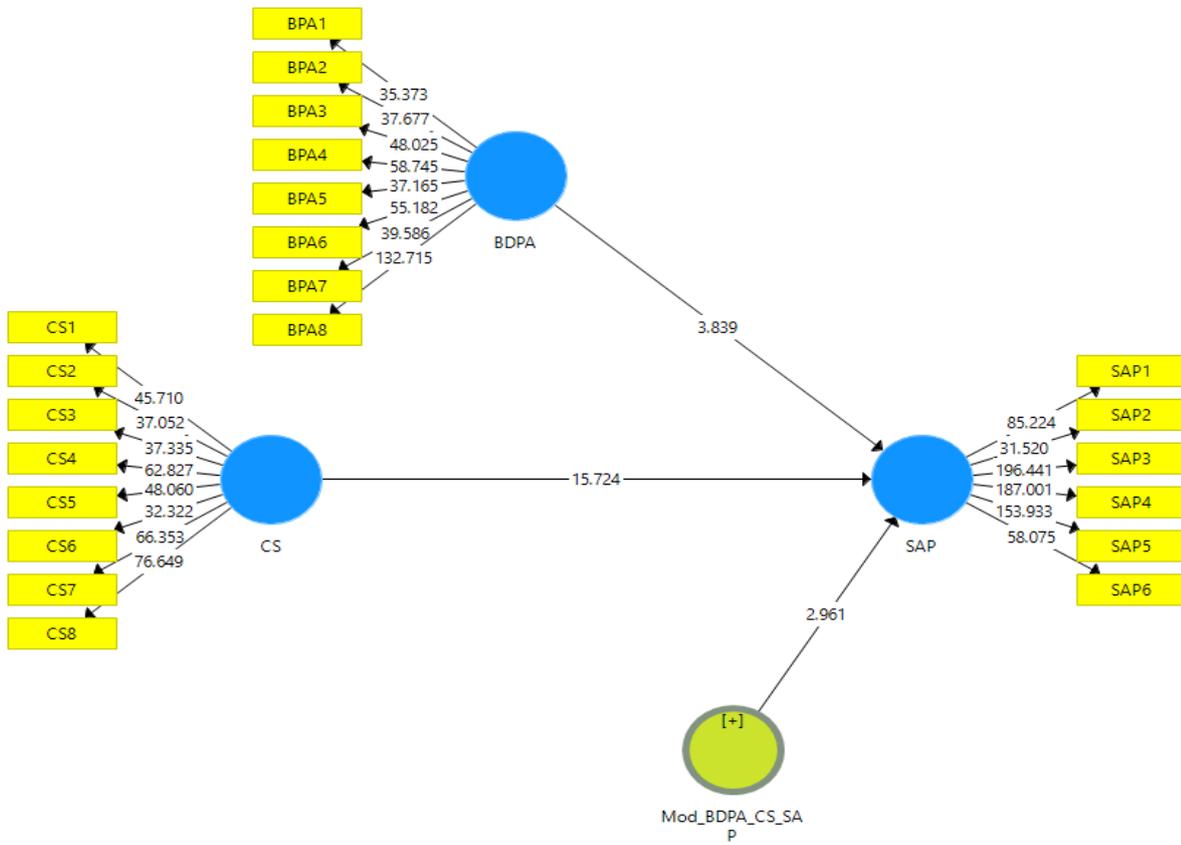


Figure 2. Showing moderation among study Variables

Figure 3 showing that big data predictive analytics strengthen the positive relationship between the competitive strategies and strategic alliance performance.

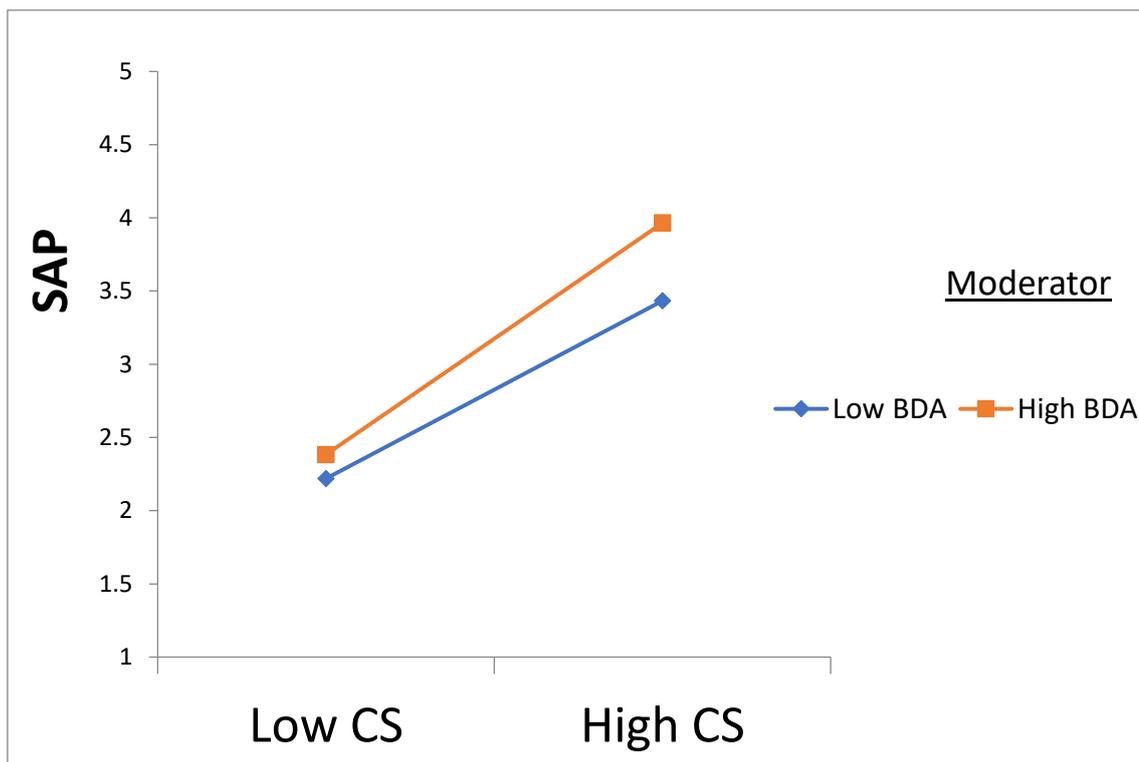


Figure 3. Showing moderating effect of BDPA between competitive strategies and strategic Alliance performance

5. Discussion

The study's objectives was to know the importance of competitive strategies, big data analytics' for the strategic alliances performance of the companies. This study untapped the relationship between competitive strategies, big data predictive analytics and strategic alliance performance. Firstly study shows that similarly, competitive strategies are the main source of strategic alliances performance in the big data environment for achieving effective marketing intelligence, these results are inline with with [5, 78] results of previous studies which also support to the findings of this study.

Furthermore, study results explains that big data predictive analytics has a positive and significant relationship with strategic alliance performance, these results are also oncurrent with the work of the previous researchers [5, 16, 79]. 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 [60]. Here, organizations can consider companies' experience in certain activities that can lead to mutual help and help each other to improve the future of the organization to get a competitive advantage [80]. Given the importance to resource-based theory and information business theory, to build avstrategic 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 [81, 82]. This explain that competitive strategies are most important for the organizations long life success [83]. All these above

arguments show that importance of the competitive strategies and big data for the strategic alliance performance for the organization. Furthermore, 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 more learning opportunities for companies. 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 [84-86].

Secondly, this research findings show that big data predictive analytics play the moderator role between competitive strategies and strategic alliance performance. These findings are consistent with the previous work of the researchers [5, 99]. All the hypotheses of the study are approved theoretically and empirically in this research which supports to the outcome of the research. .

Similarly, this study shows that the proposed model of the study was tested theoretically and empirically in this study and found significant relationships of the variables with each other. The main findings of the study are that it contributes to the theory and help the future researchers to conduct the study in some other area of study.

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 and 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 provides 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, which indicated the numerous factors of big data predictive analytics with a company's performance except for strategic alliance performance [7]. Thus, this research contributes to the literature on big data predictive analytics and strategic alliance performance. Previous researchers only linked big data predictive analytics with supply chain management [21, 87], company performance [5], and change management [21]. The current study extended the work by adding a moderator big data predictive analytics between competitive strategies and strategic alliance performance.

This research better understands that competitive strategies has a positive association with strategic alliance performance. Furthermore, big data predictive analytics is positively and significantly play a role of a moderator between competitive strategies and strategic alliance performance. This information can be used in other investigations that aim to offer new values to the big data environment. Thus this study is empirically evident that the variables used in this study could be a new way for future investigations.

5.2. *Practical Contribution*

The Study findings explained and opened new directions for the strategic alliance performance in big data environment and suggested the following main matters:

(a) big data analytics and strategic alliance performance provide a direction for the practitioners to practice the importance/use of big data analytics with the strategic alliance performance in their companies. The association between these two variables is strong and are positively affecting each other.

(b) Companies' employees truly understand the importance of big data predictive analytics with strategic alliance performance. This concept leads the organizations toward the contribution of the employees of the companies for such a strategic decision where the companies are willing to have an alliance with each other.

(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.

(d) Data mining is considered to be a built-in mechanism in big data analytics making it simple in decision-making and solving challenges, whereas information extraction is performed by machine learning and data mining. The study also explores big data analytics, which are considered to be a key in strategic alliance. In a nutshell, the integration of technologies has resulted in increased efficiency, reduced decision time, and strong real-time analytics in the current era. The study results explain that the findings have the contribution in the DM and ML. Through these process from unstructured data knowledge can be extracted and further it can be applied in different settings.

The study's main contribution is that big data is an important tool for companies' success. Companies must consider this factor for their survival and to have a 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 study 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 organizations 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 long run. This research gives a future avenue for the organization to work according to the need of the day.

6. Conclusion

The study's main objective was to investigate the relationship between big data predictive analytics, competitive strategies, and strategic alliance performance. In this regard, the study formulated four hypotheses to explain the role of big data predictive analytics, competitive strategies, 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 competitive strategies. 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 predictive analytics has a moderating role between competitive strategies and strategic alliance performance. Study findings indicated that big data predictive analytics increase competitive strategies and, in turn, it strengthens the relationship with strategic alliance performance.

6.1. Limitation and Future Research Direction

There were some strengths and limitations associated with this study. Firstly, this study contributes to the literature of 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 competitive strategies; 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 limited to the developing country context; a comparative study can be conducted on future concerns. 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 data collection like surveys, semi-structured interviews, and disclosure analysis. This study can also use the responses of the home utility as proof in future studies. This study is only limited to Pakistan's telecom sector; in future research, it is suggested to collect the data from others like the health sector, NADRA, education, or any other business organization.

Supplementary Materials: The following are available online at www.mdpi.com/xxx/s1, Figure S1: title, Table S1: title, Video S1: title.

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Appendix A.

Strategic Alliance Performance [88, 89]

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 [67, 68]

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

Competitive Strategies [69, 70]

1. In an alliance, the Company set its product cost slightly lower than other companies' products.
2. The companies concentrate on the provision of unique products different from their competitors.
3. The companies differentiate their products/services on the customer value proposition.
4. The company offers a wide range of differentiated products than its competitors.
5. The company offers a wide range of differentiated supplementary services than its competitors, such as sports centers, new internet services, and state the art library.
6. In Strategic alliance companies, research and development capabilities enhanced as a competitive advantage
7. The company is committed to ensuring high discipline but freedom and responsibility.
8. The company's unique services with more effective equipment maintenance and replacement policies.

9. The company offers unique services and maintains competitive pricing in strategic alliances.

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