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Linking Big-Data Analytics with the Pricing Strategies of E-Retailers: A Quantitative Approach

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Abstract

Studies on big-data analytics are rare, especially in Pakistan. However, in recent times, the topic has been explored continuously in the field of computing as well as management sciences. However, most of the studies are not consistent with the retail industry though the industry is one of the fastest-growing and significant in contributing to society. Therefore, the purpose of this study is to relate big data with the pricing of e-retailers to understand the relationship in the context of developing sectors. However, there are very few skilled data-specialists specialists who have appropriate knowledge in this regard, and hence the study has been conducted with a sample of sixty-five respondents. SMART-PLS has been incorporated to devise quantitative analysis which indicated that big data is significantly important in the context of e-retailing and also has the ability to improve the pricing mechanism of e-retailers.

Key Words: Big-Data, E-Retailers, Advanced Algorithms & Skilled Data Specialist

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1. Introduction:

In recent times companies are leveraged to take use information technology to implement business intelligence tools to take the competitive edge. Studies highlight Big-Data as the latest form of technology for making better business decisions especially in the field of e-commerce (Seetharaman et al., 2016). Massive development in all the sectors of information technology makes big data as the most essential resource for all the sectors. However, the use of this technology is still in the infancy stage (Yang et al., 2019). The technology is able to raise margins of the retail sector by 60% (Aktas & Meng, 2017) which contributes 6 to 7 % to the world economy & also in the growth phase. However, the completion is really stiff in the online retail segment as of real-time customer interaction, and therefore the use of big data may aid e-retailers through volume, variety, and velocity (Seetharaman et al., 2016).

In fact, Macy's i.e. US Based retailer devised a mechanism that has the ability to analyze an assortment of massive product inventory and has the capability of analyzing 73 million items in just an hour. The analysis is helpful in assuring the availability of products from a range of categories are available readily (Akter & Wamba, 2016). All of these benefits are aligned with resource-based theory (RBV) that indicating the internal resources of the firm are the real reason for its growth and competitive edge (Dhiya. 2020 & Ramadan et al., 2021). Therefore it is optimal to indicate that the bid data is the main source in the attainment of excellence in key business areas (Ramadan et al., 2021).

2. Statement of Problem & Theoretical Framework

Recent studies highlight the importance of advanced analysis tools for each and every industry. Tools provide a way to survive under difficult conditions. However one of the prior studies on the impact on big-data analytics indicated that the use of big-data might be explored in other industries than pharmaceutical. Moreover, the significance might also be understood for other variables than sales performance (Shahbaz *et al.,* 2020). Thus the selection of the retail industry is optimal for this study as retail is proving 6%-7% to the world economy (Seetharaman et al., 2016) and the use of big data may increase margins of the retail industry by 60%-70%. Though the increase in the use of big data also fosters recommendations to conduct research on choices associated with micro and macro factors that may affect the success of data analysis (Seetharaman et al., 2016). Though lacking studies on the use of this marathon technology with reference to Pakistan is not only because of lack of technology but also due to differences in culture (Sultan et al., 2020).

Thus, through considering Seetharaman et al. (2016); Shahbaz et al. (2020), and Sultan et al., (2020) further study must be conducted to explore the significance of big data with reference to the retail sector of Pakistan. This study uses the e-retailing sector of Pakistan for the analysis of results through the use of big-data technology. These parameters are done in accordance with as big data opens up new streams for the development of e-commerce. Thus, e-commerce companies must focus on the use of big data in order to analyze information adequately (Yu *et al.,* 2021). On the other side, the competition is really high in e-retailing and big data might be a really beneficial resource for e-retailers (Seetharaman et al., 2016). Therefore price has been selected as the only dependent variable for the study as it is not only included in the major operations of the retail sector but also in challenging ones (Aktas & Meng, 2017).

However, big data is really significant in dealing with day-to-day operations but the linkage of advanced algorithms is a must order to have desired knowledge regarding the dynamic effects (Aktas & Meng, 2017 & Silva et al., 2020). Thus in order to use technology effectively the skill set of data-scientists are important and therefore, used as the moderating variable.

3. Significance of the Research:

The study is one of the very few in this domain (Sultan *et al.*, 2020) and reflects the use of big data on one of the fastest-growing and important industries of the world (Seetharaman et al., 2016). Moreover study also reflects the use of big data as one of the most important elements for strategy development in the retail sector. Thus study must be termed as pervasive in nature as it highlights not only the impact of big data on the pricing of online retail but also reflect this through the use of advanced algorithms (Silva, Hassani & Madsen, 2020) and the skills of big-data scientist (Surbakti et al., 2020), as these variables have much importance in this vein. Thus appropriate to highlight the study like the one which has been done specifically to explore the impact of big data on the pricing mechanism with the reference of well-known data scientists from on retail segment of Karachi.

4. Literature Review:

Most of the research which bridges big data with the retail sector mainly focuses upon the collection of consumer insights in order to implement marketing activities accurately (Aktas & Meng, 2017). However, pricing is one of the most important and significant variables especially for companies using online mediums for conducting their business. This is evident from the strategy of Amazon as dynamic pricing that yields a 35% increase in sales is based on competitors' pricing, product sales, actions of customers & any geographical preferences (Akter & Wamba, 2016). Though pricing of products is not only included in the major activities of the retail sector but also in those functions of the retail sector which are challenging. Pricing is difficult to manage due to different SKUs as well as differences in pricing for different locations due to differences in demand and competition. Data management became more difficult when there is a promotional scheme as due to promotions price does not remain homogeneous and there is also difficult to manage historic data. Although through big data the promotional campaign can be implemented more effectively and efficiently as big data has the ability to predict the source of sales lift (Aktas & Meng, 2017).

However, there is a need to tracepoints that may provide reasonable details regarding customer preferences (Chauhan et al., 2017), and the points may be used to relate big data to related issues and problems (Silva et al., 2020). However, there is a shortage of data-scientist who have the ability to conduct these forms of complex analysis. This lacking of data-science specialists is also evident in developed countries like the USA which can be increased significantly in near future. However, human resources might be supplemented with essential education and training in order to deal with the requirements (Aktas & Meng, 2017).

5. Research Methodology

5.1 Research Design

The purpose of the study is to increase knowledge regarding the use of big-data analytics for dealing with price-related issues for e-retailers, which are in the infancy stage in Pakistan (Ali, Subzwari & Tariq, 2016). Thus suitable to relate the study with epistemology as according to Saunders Lewis and Thornhill (2009), the purpose of epistemology is to create and build knowledge. Though the concept of research onion by Saunders et al (2009), also requires a philosophical stance (research paradigm), to relate philosophy with data-analysis technique. On the other side, prior studies under this vein highlighted that quantitative analysis may make our decisions worthwhile, especially when relating big data with the challenging activities of the retail sector like pricing (Aktas & Meng, 2017). Thus, in consideration with Saunders et al (2009) and Zukauskas Vveinhardt and Andriukaitene (2018) post-positivism has been selected as the research stance which may be used for qualitative and quantitative studies. The research strategy is a survey (Saunders et al., 2009), and the time horizon is cross-sectional (Saunders et al., 2009 & Bougie, & Sekaran, 2016).

5.2 Sampling Design:

In order to increase the validity of the study, data has been compiled with the reference of data analysts working with e-retailers. Thus, followed quota sampling and also the footprints of Aktas and Meng (2017), the sampling is also treated as the best alternative of probability sampling (Yang & Banamah, 2014).

The total number of a questionnaire circulated for the study are 75 however the total number of questionnaire returned was 68 and among these, three questionnaires were not adequately filled. Therefore, a study has been done on the sample of 65 which makes the response rate 86.66 approximately equal to 87%. However, the sample size seems to be small for conducting marketing-related research hence in accordance with Pathirage Amaratunga and Haigh (2008), it is possible to conduct a study on a smaller sample size. The postulate is effective as studies with a focus on theory building approach may be synthesized with SMART-PLS for conducting statistical analysis.

5.3 Questionnaire:

The questionnaire for the study has been devised in a hybrid manner as some of the variables were used by prior studies and therefore the elements have been adapted. Although there are some parameters that were not been gauged previously in a quantitative manner, therefore, the portion related to these parameters is self-adapted. In adapted variables price has been adapted from Le and Liaw (2017), Big-Data and Advanced Algorithm Analysis from Seetharaman et al., (2016)

5.4 Software:

In sampling design, it has been mentioned that the study is based upon theory building approach and uses a smaller sample size for analysis. Therefore, in accordance with Benitez Henseler Castillo and Schuberth (2020), SMART-PLS is the best choice for data analysis.

6. Statistical Testing and Analysis

SMART-PLS uses mainly two types of models that are reflective and formative while sometimes the analysis will be hybrid models that are known as higher-order models (Afthanorhan, 2014). However, the model of this study is reflective, and therefore both of the models that are inner (measurement) and outer (structural), should be measured through Afthanorhan, (2014) and Benitaz et al (2020).

Figure 1 indicated outer loading for the entire range of elements for any of the variable are more than 0.6 thus effective to state that all the elements are legitimate to be included in the model. The postulate is true in the light of Afthanorhan (2014). Though the value will become more reliable as it approaches one (Khan, Sarstedt, Shiau, Hair, Ringle & Fritze, 2019).

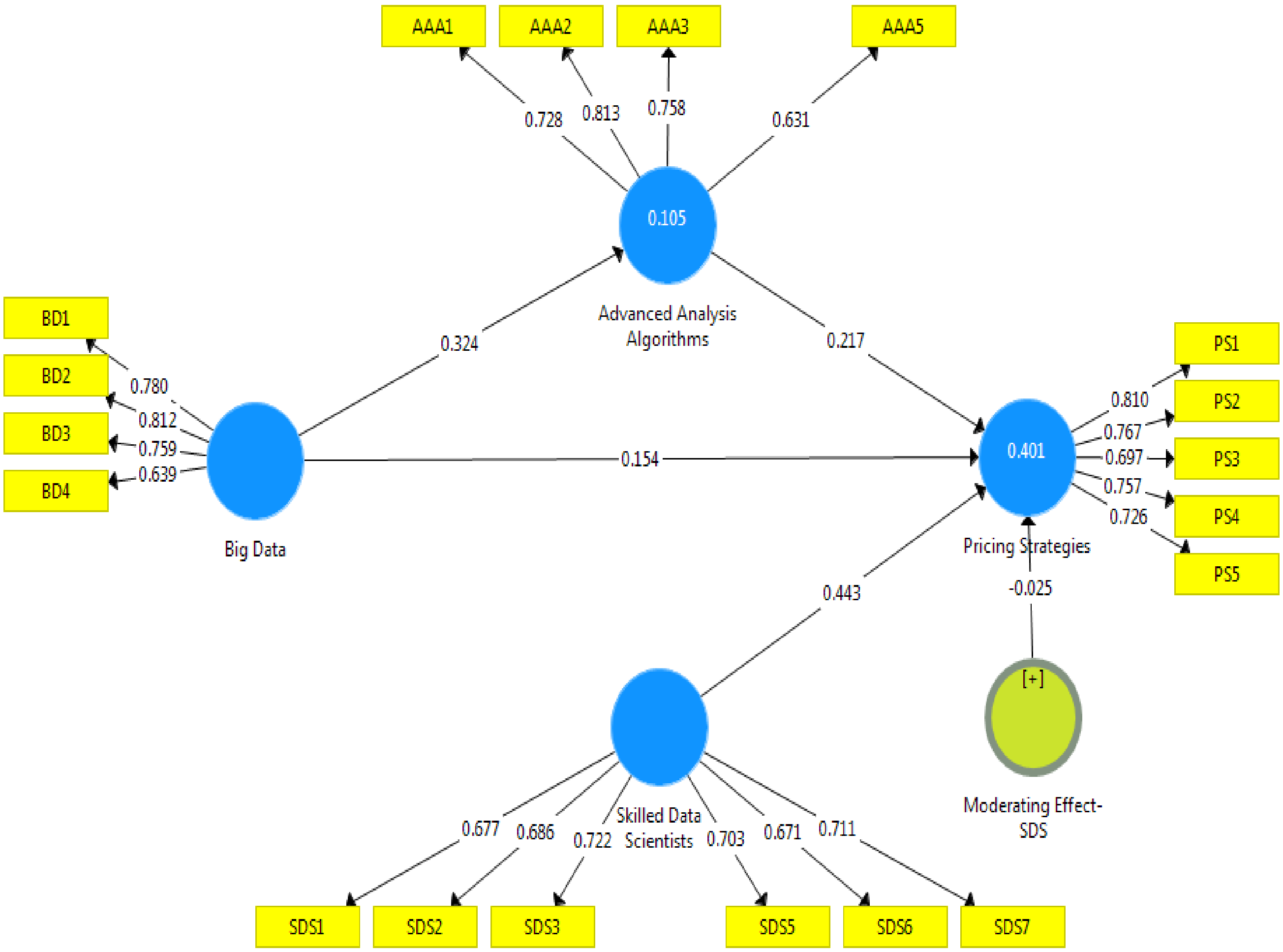

FIGURE1: Outer Loadings and CFA

R Square

	R Square	R Square Adjusted
Advanced Analysis Algorithms	0.705	0.702
Pricing Strategies	0.641	0.637

Table 1: R-Square (Predictive Accuracy or Quality Criteria)

Table 2 is indicating predictive accuracy through R^2 and this is the measure of variance caused by independent variable due to change any change in a predictor variable (Ringle, Da Silva & Bido, 2015).

This is determined through ordinary least square (Beniteze et al., 2020) and the minimum value which is required to show variance in the dependent variable is 0.26 while 0.5 is a value to show moderate relation, and 0.75 or above is used to indicate a substantial relationship (Hair, Ringle & Sarstedt, 2011). Thus the variance shaped up in mediator as well as dependent variable is significant enough to be considered.

Construct Reliability and Validity

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Advanced Analysis Algorithms	0.735	0.762	0.824	0.541
Big Data	0.740	0.756	0.836	0.563
Moderating Effect-SDS	1.000	1.000	1.000	1.000
Pricing Strategies	0.808	0.812	0.867	0.566
Skilled Data Scientists	0.789	0.793	0.849	0.691

Table 2: Construct Reliability & Convergent Validity

Table 2 is indicating construct reliability through reliability measures like Cronbach's alpha (α), Goldstein rho and composite reliability. However, Goldstein rho is better reliability evaluator as compared to Cronbach's alpha (α) **(**Ravand & Baghaei, 2016**)**. Although all of the indicating the model fitness as the values for all the indicators are higher than 0.5 (Sijtsma, 2009a&b). On the other side convergent validity has been assured through composite reliability as well as average variance extracted (AVE) though AVE alone with values of 0.5 or above may suffice to indicate convergent validity (Benitez et al., 2020). Hence the study has construct reliability as well as convergent validity.

Heterotrait-Monotrait Ratio

	Advanced Analysis Algorithms	Big Data	Moderating Effect-SDS	Pricing Strategies	Skilled Data Scientists
Advanced Analysis Algorithms					
Big Data	0.400				
Moderating Effect-SDS	0.265	0.107			
Pricing Strategies	0.462	0.491	0.131		
Skilled Data Scientists	0.345	0.489	0.113	0.686	

Table 3: Discriminant Validity

Table 3 is indicating discriminant validity in order to assure that variables used in the construct are not the same and respondents perceived these variables as different with respect to concept and as their numeric indications (Cheung & Lee, 2010). HTMT is perceived as the best tool to assure this requirement (Benitez, et al., 2020) and with any value of 085 or lesser the criterion has been fulfilled (Hair Jr., Sarstedt, Ringle & Gudergan, 2017). Hence in accordance with these parameters study also assures the discriminant validity and therefore must proceed towards inferential statistics.

Mean, STDEV, T-Values, P-Values

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Advanced Analysis Algorithms -> Pricing Strategies	0.217	0.220	0.052	4.153	0.000
Big Data -> Advanced Analysis Algorithms	0.324	0.334	0.046	7.094	0.000
Big Data -> Pricing Strategies	0.154	0.152	0.052	2.971	0.003
Moderating Effect-SDS -> Pricing Strategies	-0.025	-0.025	0.047	0.518	0.605
Skilled Data Scientists -> Pricing Strategies	0.443	0.442	0.049	9.104	0.000

Table 4: T-Statistics & P-values

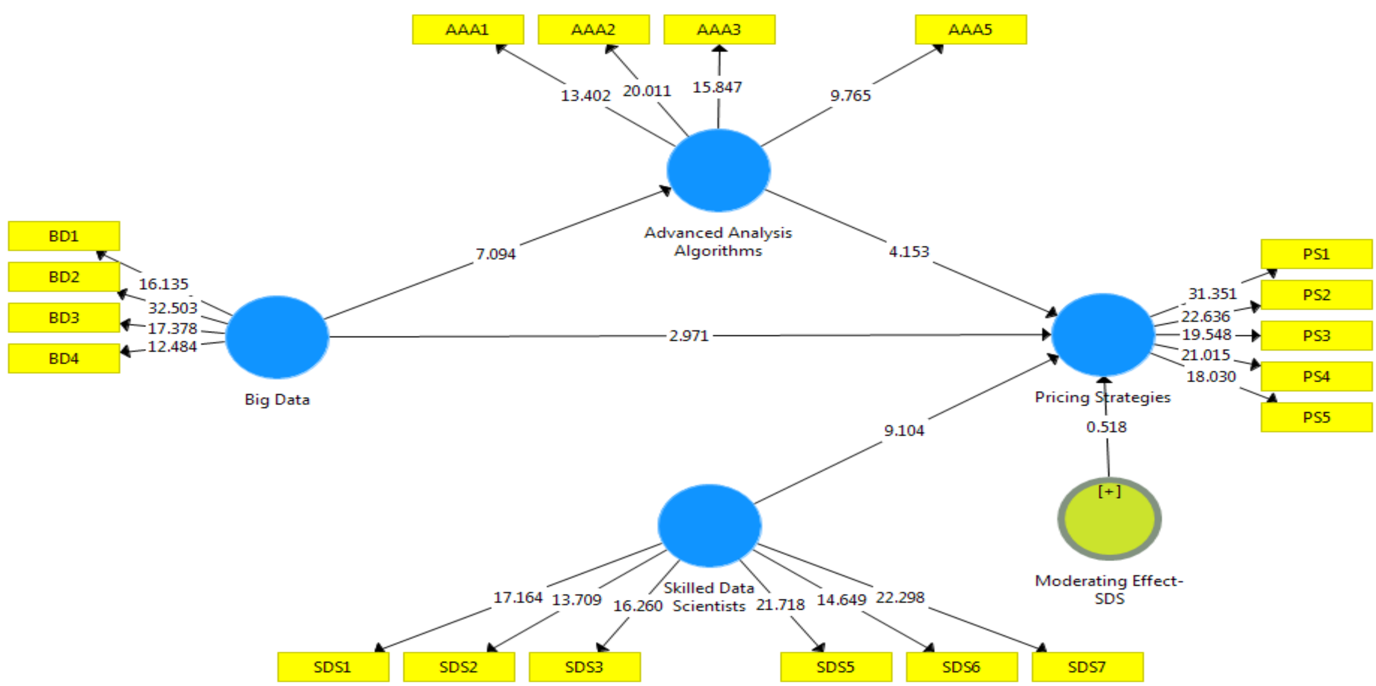

Figure 2: Boot-strapping (t-values for total effects)

Figure 2 in connection with table 4 indicates p-values and t-values to highlight inferential statistics. The impact of one variable over another can also be observed through figures as well as tables. Therefore in consideration with Durate and Amaro (2018) and Kock and Hadaya (2018) for t-statistics and p-values big-data, advanced algorithms & skilled data scientists are found to be potent predictors of pricing strategies of e-retailers. Similarly, advanced algorithms were found to be a potent mediator for creating the effect of big-data on the pricing strategies of e-retailers. Similar can be evident through figure 2 and table 4. Moreover, moderation of skilled data scientists does not have any impact on the pricing strategies of e-retailers.

8. Conclusions and Discussion

This study worked on the point indicated by Seetharaman et al. (2016), to work on the impact of big data on strategies of retailers. This does not only aligns with Yu et al (2021) but also fulfills the lacking of research indicated by Sultan et al (2021). Moreover, selection of price for assessing the impact of big-data on strategies of e-retailers is not only aligned with Aktas and Meng (2017), but also increases the significance and application of this study significantly as pricing has significant importance for the retail industry and it is also included in the list of challenging elements (Aktas & Meng, 2017). However, as far as the resemblance is concerned to study is aligned with Seetharaman et al. (2016) and Silva et al. (2020) as big data is proved to be a resource that may affect pricing strategies of the e-retail sector.

However, these strategies may further be optimized by using advanced algorithms. Hence study is potent to prove the role of advanced algorithms in applying big data and also for highlighting advanced algorithms as the mediator between big data and pricing strategies (Silva et al., 2020). Similarly, the study is also consistent with Aktas & Meng (2017) that skilled data-scientists are required to deal with big-data technology. Though using this variable as the moderator is insignificant that may highlights that big data is the tool that is effective for analyzing sales performance as indicated by Shahbaz et al. (2020),

9. Areas for Future Research

This study tries to highlight the impact of big-data analytics on the pricing strategies of the e-retail sector. However, the data has been collected from data-scientist mostly from those organizations which are operating from Karachi.

Therefore comparing the perception of data-scientist from different cities as well as different countries may lead to better research. Similarly, findings the impact of skilled data-scientist on sales performance through meditation of advanced algorithms may also optimize learning with reference to the e-retail sector. Last but not least the model can also be tested with the reference to different sectors in which e-retailers are operating. Thus comparing the analysis on the basis of the sector may also be a better way to increase the level of understanding.

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