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Application of big data analytics and organizational performance: the mediating role of knowledge management practices

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Abstract

Drawing from tenets of the resource-based theory, we propose and test a model that examines the relationship between the application of big data analytics (ABDA) and organizational performance (OP) in small and medium enterprises (SMEs). Further, this study examines the mediating role of knowledge management practices (KMP) in relation to the ABDA and OP. Data were collected from respondents working in SMEs through an adapted instrument. This research study adopts the Baron–Kenny approach to test the mediation. The results indicated that the ABDA had a positive and significant impact on OP. Also, KMP had partially mediated the relationship between ABDA and OP in SMEs. The dataset was solely comprised of SMEs from Pakistan administered Kashmir and may not reflect the insights from other regions. Hence limits the generalizability of the results. Findings highlight both strategic and practical implications related to decision making in organizations for top management, particularly in developing countries. This study attempts to contribute to the literature through novel findings and recommendations. These fallouts will help the top management during the key decision-making process and encourage practitioners who seek competitive advantage through enhanced organizational performance in SMEs.

Keywords: Application of big data analytics, Knowledge management practices, Organizational performance, SMEs

Introduction

Over the past decade, the application of big data analytics (ABDA) has been widespread research interest among researchers and practitioners [1]. According to contemporary studies, across a wide range of industries, the ABDA is a key driver of organizational success [2]. Furthermore, there is rapid progress in the acknowledgment by the executives about the potential benefits linked with the ABDA [3–5]. The annual public and private investment in the application of big data analytics has highly increased up to billions of dollars across the globe [6–8]. Due to high strategic and operational potential, the ABDA can improve the efficiency and effectiveness of business and act as a game-changer [1, 9]. High-performing organizations consider the ABDA as a critical differentiator and significant factor for their growth [10–13].

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The experts of big data analytics [14], provided deep data-driven insights [3], about the competitive advantages gained by organizations [15–18]. Notably, big data analytics is considered the "fourth paradigm of science" by a few scholars and practitioners [19, 20]. Likewise, [21] argued that big data analytics is a "new paradigm of knowledge assets", and the next innovative, competitive, and productive frontier [22]. High-performing organizations consider the ABDA a key to growth and critical differentiator [1, 10, 12, 23].

Despite this prevalent importance and research interest, examining the relationship between the application of big data analytics and organizational performance (OP) through empirical studies remained scarce [24–27]. There is significant evidence that big data has been incorporated into the academic world but little has been done to link it to knowledge management practices (KMP) e.g. [28–30]. So far, very few rigorous and larger-scale studies have been conducted to examine how the ABDA can enhance OP [23]. Moreover, to reveal the insights about this research gap it is required to empirically explore the link between the ABDA and KMP [31].

To address this gap in literature we proposed a model drawing from the tenets of the resource-based theory [32] explaining, how the link between the elements of an organization like data, analytical tools, knowledge management practices creates value, increases efficiency and eventually effect the organizational performance. Organizations can get a competitive advantage through efficient usage of their resources [33, 34] but all resources are not of equal value. In practice, it is difficult to understand the relation between successful strategies and sources of advantage [32]. To get a competitive advantage, it is necessary to identify, understand, and classify the core competencies. Therefore, this study aims to examine the relationship between the ABDA, KMP and OP in SMEs.

This study contributes to the existing literature in three folds. First, we examine the effect of the ABDA on OP which has been neglected in previous studies. Second, we explore the mediating effect of KMP on the relationship of the ABDA and OP, which will improve the capability and efficiency of managing knowledge assets [35, 36]. Third, the vast majority of the literature related to big data and knowledge management addresses the context of advanced countries only, whereas, the theoretical and practical implications of these factors linking organizational performance in developing countries like Pakistan has highly been ignored.

Literature review and hypotheses development

Big data analytics

Big data analytics refers to an assortment of a large volume of data and technology which is gathered from different sources, and make it possible for a business to gain an edge over their rivals through enhanced business performance [37]. Goes [38] defines the concept of big data as huge volumes of numerous observational data used in the decision-making process. Schroeck and Shockley [12] described big data (BD) as real-time information, media data nontraditional form, IT-driven data, social media, and huge volume data. While 'Variety' and 'Volume in Big Data' have got significant consideration [14, 39]; whereas many studies highlight the vital roles of Veracity, velocity [6, 40, 41]. Here it is pertinent to mention that analytical skills and tools are the essential 'components' for big data analytics (BDA) [17, 42]. Sun and Xu [43] defines big data analytics as the procedure of accumulating, consolidating, scrutinizing, and exploiting large sets of data from heterogeneous and autonomous resources, to determine patterns and other expedient information to make improved managerial decisions.

Furthermore, Cao and Chychyla [44] describes BDA as the technique of determining and accomplishing considerable measures from big data to backing decision-making. BDA contains various tools to inspect data that organizations acquire from internal and external resources to identify substantial patterns. According to McAfee and Brynjolfsson [45] BDA is a prospective value-creator that several enterprises are adopting for getting assistance in the decision-making process. Big data analyst requires competencies to find out implications, and develop intuitions [14, 46]. Effective execution of BDA required appropriate analytical tools for scrutinizing [44]. The BDA addresses the latest systematic procedures for solving complications of business, which was not possible earlier due to the scarcity of data or analytical tools [17, 47].

Knowledge management practices

Knowledge management practices facilitate the systematic procedure of knowledge creation, acquisition, conversion, and application [48–50]. KMP involve the acquisition, storage, distribution, and application of knowledge [51]. Nonaka and Takeuchi [52] described that knowledge creation is an essential part of KM theories and practices involving four stages of conversion containing tacit and explicit knowledge. Bock and Kim [53] considered that knowledge is the power that helps in solving organizational problems. KMP is the process of acquisition, conversion, evaluating, retrieving, and sharing the knowledge resources for improved and effective organizational performance, and stimulates growth and competitive advantage [54]. Organizations have great concerns about creation and management of knowledge for the enhancement of their business performance.

Organizational performance

Organizational performance refers to the capability related to the accomplishment of its goals and stakeholders' expectations along with market survival [55, 56]. It can also be defined as the process of analyzing and measuring the organization's outcome against its objectives and goals, which involves a comparison of real results with desired results [57, 58]. The OP involves actual productivity or outcomes of the organization compared with the desired outcome or objectives. Teece [59] emphasized that higher performance is contingent on the capability of the organization to cope with innovation, protect, and use intangible knowledge assets in a way that they will give benefits to the organization. Furthermore, OP can also be defined as the process of making sure that the organizational resources are being properly used and involves all the actions or activities performed by the managers of different levels in organizational hierarchy, in order to measure the extent to which an organization has achieved its objectives [57, 58].

Application of big data analytics and organizational performance

A large number of different analytical software tools are available in the market which can be used by the application of big data analysts to improve organizational performance and to make better business decisions which leads an organization towards success. A firm needs to get an analytical insight into a huge volume of data to apply big data analytics which will certainly help an organization to improve business performance [19, 60]. The famous example which will support this argument is "Amazon", which is a firm generating 35% of purchase from personal recommendations to customers based on big data analytics [61].

The ABDA is a prospective value-creator for business [45, 62] and the effective implementation of big data analytics involves essential expertise for handling big data, extract what does data means, and develop insights from the use of data [14, 63]. The 91% of the companies are investing in big data analytics as compared to the previous year's 85% indicated by the latest study on Fortune 1000 companies [64, 65]. The ABDA is considered as a tool for the perfect management of organizational assets and monitoring of business process [66, 67]. It strengthens the supply chain, improves the industrial automation and manufacturing [68], and enhances the business transformation [1, 69].

Columbus [70] described that "87% of businesses consider the ABDA a tool to achieve competitive advantage in coming 3 years and 89% believe that risk of losing market share for companies not using big data analytics is higher than companies using it. The ABDA is not only a technological advancement but also an entirely operational paradigm [71]. Business decision making based on data and information rather than intuition [11, 72]. Likewise, by adopting analytical approach organizations can get a competitive advantage and can accomplish their objectives in a better way [73].

The ABDA is positively related to successful customer's deployment and superior organizational performance [74]. There is a significant impact of the quality of analytic tools on data and or information authenticity, business decision making process that leads to OP [75]. Moreover, BDA is used to differentiate between high and low performing organizations, consequently those firms who use big data analytics become proactive and future-oriented and reduce their customer acquisition cost by 47% and increase their firm revenue about 8% [76]. In recent years, due to the ability of 5–6% advanced efficiency and profitability, the ABDA has got vital consideration on the corporate agenda [65]. Therefore, BDA can construct the benefits for any organization by improving its performance (financial performance, marketing performance, partnership performance) and competitive advantage [1, 2, 12, 65, 77, 78]. Hence, the ABDA can lead to improving organizational performance [79].

H1 There is a positive relationship between application of big data analytics and organizational performance.

Application of big data analytics and knowledge management practices

Big data analytics refers to the strategy of analyzing a large volume of data gathered from diverse sources in an unstructured, semi-structured, or structured form by using different analytic techniques. In a study [80] described the big data in term of Volume, Velocity, and Variety, whereas, knowledge has been divided into different categories like tacit, explicit (knowledge expressed and recorded as words, numbers, codes, formulas, and musical notations), implicit (gained through incidental activities), complex, and simple

[52, 81–83]. The Important feature of the BD collected from a wide variety of sources is that it can be helpful to discover hidden knowledge and generate new knowledge which in turn gives an output in the form of enhanced knowledge management (knowledge acquisition, knowledge conversion, knowledge application) through data analytics. The data collected through various sources in the structured, semi-structured, and unstructured form, if properly analyzed can help the organization to generate valuable knowledge for improved organizational decision making [84, 85]. Big data analytics provide managers a valuable perception of their business activities and application of acquired knowledge through BDA can lead an organization towards value-driven decisions [2, 86].

Knowledge management practices effectively and efficiently create knowledge with the help of the application of big data and analysis techniques. Different indications from literature suggesting the fact that the use of big data processing and its analysis can harness greater value for organizations in developing knowledge management [22, 87]. Before finding out how this big data is transformed into knowledge, it should be comprehended further. It is created from the use, analysis, and productive utilization of data and information and there are explicit knowledge and tacit knowledge [52, 82, 83, 88]. To generate more values in any aspect of their business, BD can help organizations and if an organization intends to get analytical insights into large volumes of data, the ABD technology may leverage the business aptitude extracted from the data to enhance organizational performance [18, 19, 89, 90]. Big data analytical applications create meaningful information (organize or structure) which has a greater impact on the firm for observing trends and patterns. Some actionable knowledge is generated by feeding such information into business intelligence tools to interpret the data through the analysis performed by data analysts. Such similarities provide better insights into the relationship between big data and knowledge management [31]. Therefore, the knowledge which is generated through performing analytics on big data gives escalation to effective and efficient decision making which indicates that there is a relationship between KMP and ABDA [88, 91]. This leads to the next hypothesis, that;

H2 There is a positive relationship between application of big data analytics and knowledge management practices.

Knowledge management practices and organizational performance

The effective utilization of natural resources and tangible assets is not sufficient to achieve enhanced performance, but another essential factor is effective knowledge management practices Lee and Sukoco [92]. Knowledge is an asset which linked with the overall organizational performance [93, 94]. Knowledge management is a process which reflects strategies for acquisition and creation of knowledge, either externally or internally, sharing the preserved knowledge within the firm, and the application of knowledge [51, 95, 96]. Organizations are utilizing the KMP and moving towards knowledge-driven systems to improve their competitiveness and values [97–101].

Karimi and Javanmard [102] emphasize the utilization and management of knowledge within an organization. For this purpose, first, it is essential to understand the nature of knowledge. Tacit knowledge and explicit knowledge are two fundamentals of knowledge [96, 103]. According to Davenport and Prusak [104], tacit knowledge is difficult to understand and transfer to another person. It is evaluated in the form of competencies, expertise, and concepts that individuals may possess mentally. Furthermore, Coulson-Thomas [105], added that this type of knowledge is difficult to transfer, because one of the means of transferring this knowledge, is transmission to other people in the organization through experience, practice, feelings, and attitudes with others. Whereas, explicit knowledge is easy to understand and transfer because it can be articulated easily, expressed, and recorded as words, numbers, codes, formulas, and notation [106, 107]. Explicit knowledge expressed using common language and codes. It is completely moveable and easy to share [108]. Tacit knowledge, on the other hand, is subjective and informal [52, 109]. In knowledge-intensive growing organizations tacit knowledge continuously getting attention from human resource professionals [110].

It is accepted reality that organizations used to achieve the goals through effectiveness and efficiency [57, 111, 112]. Therefore, organizations have to explore and understand the process of knowledge sharing to better deal with knowledge management [113]. Certainly, in the literature of knowledge management, the significance of knowledge sharing linked with organizational performance is extensively recognized [114–116]. In a study, Bock and Kim [53] stated that one of the most important functions of knowledge management is the encouragement of knowledge sharing, which is fundamental to knowledge creation and innovation that enables better utilization of current knowledge [52, 107]. Field managers and researchers had given importance to study knowledge sharing and transfer [117] and the connections between knowledge management and organizational performance [118, 119]. In another study, Bose [120] found that the relation of KMP and OP "financial performance, marketing performance, partnership performance" is highly associated with the organizational ability to accurately identify the effectiveness of knowledge management to acquire a market position. Therefore, proper utilization of knowledge results in better OP [121]. Furthermore, it is now believed that KMP can lead to better OP along with the much-needed innovation [122, 123]. Therefore, based on these evidences, our next hypothesis is;

H3 There is a positive relationship between knowledge management practices and organizational performance.

The mediating role of knowledge management practices

The identification of the similarities and synergies among the emerging field of big data analytics and highly established field of knowledge management is the objective of this research study. To enhance maximum efficiency by managing available knowledge assets is the basic purpose of knowledge management practices [35]. Nowadays, one of the critical success factors is the organizational ability to transform the data and information for knowledge-based decision making in all sectors [72]. In a study Chen and Mao [124] argued that to improve OP, enterprises can generate knowledge by using BDA. In other words, to gain competitive advantage, enhancing organizational performance, and capturing more market share, the ultimate goal is to create more organizational knowledge by implementing ABDA. Big data analytics can be utilized to generate new knowledge and discover hidden knowledge for better decision making that leads to enhanced organizational performance [125]. Big data analysts can help in better knowledge management, which results in a successful business [31]. Thus, it leads to the next hypothesis;

H4 Knowledge management practices mediates the relationship between big data analytics and organization performance.

Method

Sample and data collection

Various types of SMEs are currently working in Pakistan. The literature describes small and medium enterprises as informal businesses possessing flexible structures, reactive nature, and resource limitations [127, 128]. Eventually, it is accepted that small enterprise is not a slightly big business [129], with strategic orientation and organizational size being important factors impacting its behavior and performance [130], and reaction to extremely formalized market intelligence data [128]. These businesses are supported by innovative techniques and tools for data storage and consumption. To make sure the wide range of small and medium enterprises representing this study, the second author personally collected data through simple random sampling. The target respondents encompassed business owners, executives, managers, and other relevant employees who can respond to big data analytics and knowledge management practices. 230 questionnaires were distributed. The response rate was moderately encouraging, with a total of 210 questionnaires filled and returned. This response rate might look extraordinary, but in a country like Pakistan, if you are enthusiastic and have motivation with good personal references, this response rate is not unusual.

Measure validation

The instrument used a 5 point Likert scale for data collection, with 1 representing "strongly disagree "and 5 representing "strongly agree."An 11-item scale developed by Thirathon and Wieder [131] was adapted to measure the big data analytics with an alpha reliability of 0.89. Knowledge management practices were measured by using an adapted 21-item scale developed by Gold and Malhotra [98] with an alpha reliability of 0.97. The organizational performance was also measured with an adapted 10-item scale developed by Emden and Yaprak [132] with an alpha reliability of 0.94.

Descriptive statistics

Figures 1 and 2, are depicting the descriptive statistics of the sampled data, e.g. age of SMEs, and sector of production. After the exclusion of missing data, a total of 210 questionnaires has been considered for further analysis.

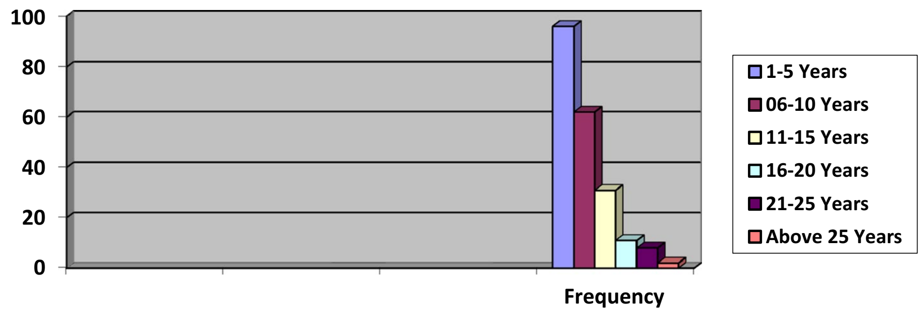

Fig. 1 Age group of SMEs

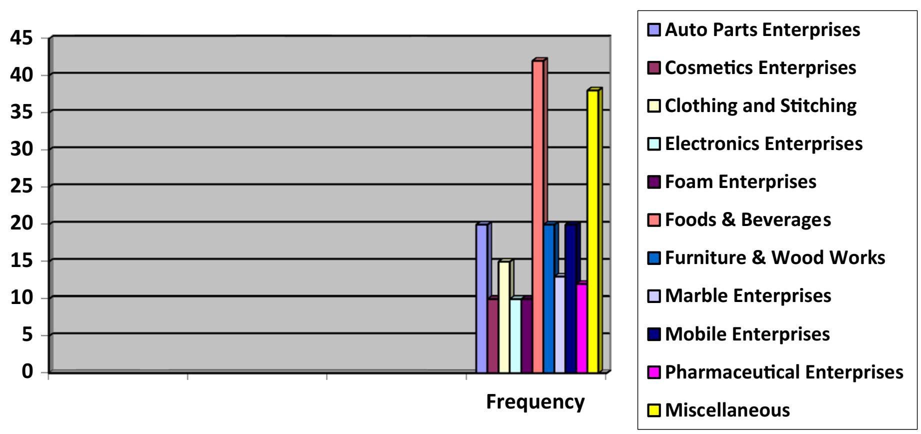

Fig. 2 Nature of SMEs (Source: Data collected from 210 SMEs)

Table 1 Kurtosis and skewness

	Mean	SD	Skewness	Std. error of skewness	Kurtosis	Std. error of kurtosis
BDA	2.9351	.64316	−.262	.168	−.518	.334
KM	3.7472	.90344	−1.222	.168	.150	.334
OP	3.6210	.93805	−.251	.168	−1.146	.334

BDA Big data analytics, *KM* knowledge management, *OP* organization performance

Table 2 Kolmogorov–Smirnov and Shapiro–Wilk tests

	Kolmogorov–Smirnov			Shapiro–Wilk		
	Statistic	N	Sig.	Statistic	N	Sig.
BDA	.127	210	.000	.968	210	.000
KM	.220	210	.000	.799	210	.000
OP	.103	210	.000	.937	210	.000

BDA Big data analytics, *KM* knowledge management, *OP* organization performance

Table 3 Reliability analysis

Name of variables	No of items	Cronbach's alpha
Big data analytics	11	.89
Knowledge management	21	.97
Organization performance	10	.94

Table 4 Correlation analysis

Variables	Big data analytics	Knowledge management	Organization performance
Big data analytics	1		
Knowledge management	.726**	1	
Organization performance	.587**	.740**	1

**Correlation is significant at 0.01 levels, N: 210

Analysis and results

Normality test

The normality of data was analyzed based on the value of Skewness and Kurtosis (Table 1). The values of skewness and kurtosis between −2 to +2 are considered acceptable for the normality of data [133].

Further, to confirm the normal data distribution analysis were done through Kolmogorov–Smirnov and a Shapiro–Wilk test. Table 2 depicting that static values of all variables in both tests were significant at a 95% confidence interval for the mean, which revealed that data was normally distributed. Parametric tests must use if data shows the normal distribution.

Reliability analysis

The Cronbach's alpha values of all variables were within an acceptable range, as Cronbach's alpha was 0.89 for the application of big data analytics, 0.97 for the knowledge management practices, and 0.94 for the organizational performance which were above the recommended value of .70 [134–136]. Thus, based on results, it was concluded that adaptive instruments had good reliability (Table 3).

Correlation analysis

The correlation Table 4 shows the level of association and direction of the relationship among the variables. The highest value of correlation coefficient ($r = .740$, $p < .01$) between knowledge management practices and organizational performance, followed by, between the application of big data analytics and knowledge management practices ($r = .726$, $p < .01$) and finally between the application of big data analytics and organizational performance ($r = .587$, $p < .01$). Results of correlation analysis revealed that all variables were significantly correlated and no multi-co-linearity problem. According to Hair et al. [137] pointed out that the correlation coefficient (r) must not go beyond .90 to get rid of the multicollinearity problem.

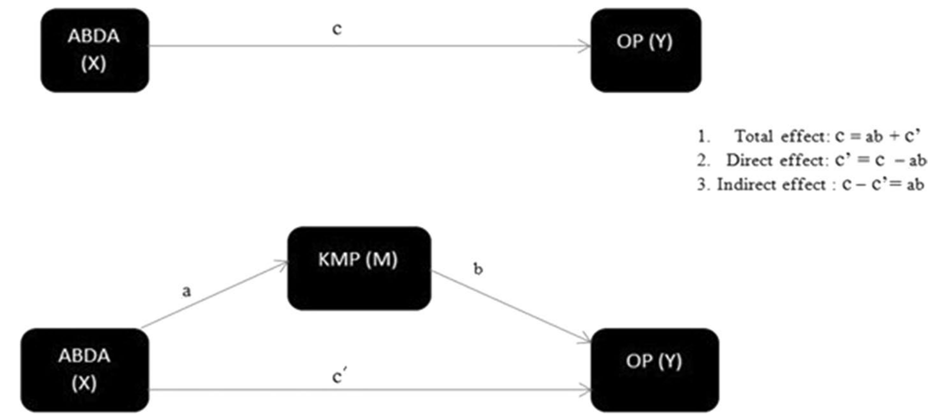

Fig. 3 Details from Baron and Kenny's [126] mediation model

Table 5 Regression of Big data analytics on organization performance through knowledge management (steps according to Baron and Kenny [126])

Unstandardized coefficients		Standardized coefficients				
Step dependent/ independent variables	B	Standard error	Beta	t	Significance level	Durbin Watson
Step 1. Dependent variable: organization performance						
(Total effect) Big data analytics	.856	.08	.587	10.446	.000	1.744
R = .587, R2 = .344, F(1, 208) = 109.127						
Step 2. Dependent variable: knowledge management						
Big data analytics	1.019	.067	.726	15.215	.000	1.506
R = .726, R2 = .527, F(1, 208) = 231.492						
Step 3. Dependent variable: organization performance						
Knowledge management	.769	.048	.740	15.884	.000	2.243
R = .740, R2 = .548, F(1, 208) = 252.289						
Step 4. Dependent variable: organization performance						
(Direct effect) Big data analytics	.152	.098	.104	1.543	.124	2.229
R = .744, R2 = .553, F(2, 197) = 128.171						

Regression analysis

Regression analysis were used to test all the hypothesis from H1 to H4. Therefore, to test the mediating role of knowledge management practices between the relationship of application of big data analytics and organizational performance, we employed [126] four-step process depicted in Fig. 3. Results of basic linear regression in step 1 and step 2, whereas multiple regression in step 3 and step 4 as suggested [126, 138], are reported in Table 5. H1 suggested that there is positive effect of the application of big data analytics on organizational performance. Step one of Table 5 sought to determine if the application of big data analytics was a significant predictor of organizational performance or not. When organizational performance was regressed on the application of big data analytics, as displayed in Table 5, application of big data analytics demonstrated a direct effect on organizational performance ($\beta = .587$, $p < .01$), and accounted for 34%

of the total variance of organizational performance. F (1, 208) = 109.128 is greater than the table value of F, and also the value of Durbin-Watson (1.744) is supporting H1. So, hypothesis 1 has accepted. In the second step as depicted in Table 5, it was sought to determine the relationship between application of big data analytics and knowledge management practices. When knowledge management practices were regressed on the application of big data analytics, it was found a positive relationship where ($\beta = .726$, $p < .01$). However, the application of big data analytics accounted for 52% of the total variance of knowledge management practices. F (1,208) = 231.492 is greater than the table value of F. Also value of Durbin-Watson (1.506) supports H2. In the third step as depicted in Table 5, we sought to understand the relationship between knowledge management practices and organizational performance. After regressing organizational performance on knowledge management practices, it was found a positive relationship, where ($\beta = .740$, $p < .01$), however, it is noted that knowledge management practices accounted for 54% of the total variance of organizational performance. Also, F (1, 198) = 252.289 is greater than the table value of F and also the value of Durbin-Watson (2.243) support H3. So, our hypothesis no. 03 has also accepted. The purpose of the first 03 steps is to establish the existence of zero-order relationships among the variables. Although this is not always true researchers usually conclude that if any single non- significant relationship found, mediation may not be possible [139]. Hypothesis 04 suggests the mediating role of knowledge management practices exists in the relationship between the application of big data analytics and organizational performance. Step four of Table 5, shows the direct effect of the application of big data analytics on organizational performance, after controlling the mediating variable, ($\beta = .104$, $p > .01$). This is a considerable reduction from the total effect of 0.587. Furthermore, after controlling mediator (knowledge management practices), big data analytics accounted for 55.3% of the total variance of organizational performance which is higher than before controlling knowledge management practices. Hence, hypothesis 4 has accepted.

Discussion and conclusion

In this study, drawn from the assumptions of the resource-based theory, a model was purposed and tested intended to explain the relationship between the application of big data analytics and knowledge management practices to determine organizational performance. The major purpose of this study was to evaluate the impact of the application of big data analytics on organizational performance through the mediating role of knowledge management practices. To test the mediating relationship, four steps method presented in research [126] is used in this study. Researchers usually conclude that if any single non-significant relationship found, mediation may not be possible [139].

Significant and positive results are found in all the steps. In first step, the impact of application of big data analytics on organizational performance is found positive and significant. This finding is in line with the previous literature. For example, in a study, Ji-fan Ren and Fosso Wamba [140] also acknowledged the positive impact of the application of big data analytics on organizational performance. Likewise, in the second step, the impact of the application of big data analytics on knowledge management practices is found positive and significant. This outcome is also in line with the findings of the previous study [141]. Similarly, in the third step, the impact of knowledge management practices on organizational performance is found positive and significant. This finding is also supported by previous literature, for example in a study [142] found that knowledge management practices have a positive and significant impact on organizational performance. Furthermore, in step 04 the mediating role of knowledge management practices between the relationship of application of big data analytics and organizational performance is found positive and significant. Here, after controlling mediator (knowledge management practices), application of big data analytics accounted for 55.3% of the total variance of organizational performance which is higher than before controlling knowledge management practices. Also, there is a considerable reduction from the total effect of 0.587. According to [126] in step 04, when the effect of the mediator on the dependent variable is controlled, if the result depicts the reduction in correlation between independent and dependent variables, there is partial mediation.

Therefore, it infers that knowledge management practices partially mediates the relationship between the application of big data analytics and organizational performance. This insight is a unique contribution in existing literature, which is drawn from the consolidated model based on the relationship of application of big data analytics, knowledge management practices, and organizational performance.

Theoretically, this research study advances the literature on organizational performance by explaining the mediating role of knowledge management practices between the relationship of the application of big data analytics and organizational performance. From this study, several key findings emerged that are important for theory, research, and practice. Hence, in addition to the direct relationship between the application of big data analytics and organizational performance, this study suggests that knowledge management practices play a partial mediating role, which is a unique finding of this study and has never been tested before in the big data and organizational performance literature, in the context of SMEs in any developing country. Therefore, vital contribution of this empirical study in literature is to identify the mediating effect of knowledge management practices in the relationship between the applications of big data analytics and organizational performance.

Theoretical implications

Based on the existing literature, organizations are highly concerned to identify and recognize the practices that can enhance their performance and provide them with a competitive advantage [143]. Hence, enthusiastically following the adaption along with the implementation of innovative techniques and activities, such as application of big data analytics is becoming essential as enterprises are facing internal and external pressures to get involved in such activities. As hypothesized, big data analytics was statistically significant in explaining organizational performance, both with and without the mediating role of knowledge management practices. Our research helps to uncover how big data analytics can contribute to organizational performance, by demonstrating the important role of knowledge management practices. Big data analytics is conducive to the deployment of knowledge management activities, which results in a significant contribution through enhanced organizational performance. This implies that the positive effect of the application of big data analytics on organizational performance will robust when the organizations facilitate knowledge management activities.

Managerial implications

This study recommends several suggestions for researchers, practitioners, managers, and decision-makers. First, the key drivers (i.e. application of the big data analytics and knowledge management practices) of organizational performance are identified. Understanding these vital factors will help decision-makers to devise strategies and overcome the performance-based challenges. Big data was acknowledged by Davenport and Patil [14] as the next big thing in the twenty-first century. Whereas, Cao and Chychyla [44] explained big data analytics as the technique to determine and manage valuable information, patterns, or conclusions from big data to support managerial decisions. Therefore,it infers that big data analytics can present the insights after mining the hidden patterns to support innovation, more appropriate and real-time decisions, value creation, and subsequent improvement in organizational performance [22]. Thus, both practitioners and academics continue to motivate studies on big data analytics which has high operational and strategic potentials in transforming business. Furthermore, these insights can help decision-makers to successfully promote knowledge management practices in their organizations, and increase their commitment to utilize big data and knowledge management practices, which are essential factors for organizational success. Finally, this study identifies the effects of big data analytics on organizational performance as a competitive advantage for SMEs. Hence, this study adds valuable knowledge for managers related to the successful implementation and benefits of big data analytics and knowledge management.

Limitations and future research directions

The main limitations of this study are the use of the cross-sectional method of data collection, as well as only a uni-level model, is proposed and tested. Multi-level modeling can produce better insights into the phenomenon and recommended in future research. Moreover, longitudinal study and or data collected in time lags will give more deep insights and generalizable results. So, while testing this proposed model these methods are recommended in future research. Another limitation of this research study is only one mediator in it i.e. knowledge management practices. The possible area of future research can be the study of other mediators in this context. Furthermore, exploring the role of moderators' e.g. managerial commitment in this context may add value in study and result in novel insights. Though, this study entails vital insights about two significant measures of organizational performance (i.e. application of big data analytics and knowledge management practices) in SMEs by testing the proposed framework, it is recommended to study whether the proposed framework differs in other sectors as well as in different contexts or not. Therefore, a comparative study of the proposed framework in other countries and organizations may produce better insights about different key factors that also influence organizational performance.

Abbreviations

ABDA: Application of big data analytics; BD: Big data; KMP: Knowledge management practices; OP: Organizational performance; SMEs: Small and medium enterprises.

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Not applicable.

Authors' contributions
In this study, MQ was the main contributor in all phases from start to end except for data collection. BG was assisting MQ during all phases of this study. Moreover, BG had a vital contribution to data collection and drafting of the article. All authors read and approved the final manuscript.

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Availability of data and materials
The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Competing interests
The authors (MQ & BG) declare that they have no competing interests. Where MQ is Muhammad Qasim Shabbir and BG is Syed Babar Waheed Gardezi.

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