The effect of supply chain connectivity and task technology fit on efficiency: Exploring mediating role of big data analytic

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CHRONICLE	ABSTRACT
	It is essential to improve the efficiency of hospitals, especially in the situation of Covid-19. Therefore, the primary purpose of this paper was to examine the effect of supply chain connectivity, perceived ease of use, and task technology fit on big data analytics and efficiency. This study assessed the mediating role of big data analytics as well. A survey questionnaire was developed to collect the data. The data was collected from the employees working in the hospitals of the UAE. For this purpose, convenient sampling was adopted. The questionnaire was adapted from past studies. The questionnaire was distributed among 426 employees. The usable response rate was 73.22%. The gathered data was assessed using PLS 3. The study's findings confirmed the direct effect of supply chain connectivity, perceived ease of use, task technology fit on big data analytics, and efficiency. This study also revealed the significant effect of big data analytics on efficiency. Moreover, the mediating role of big data is also confirmed in the present study. This study fills several theoretical and managerial gaps mentioned. The study's findings are helpful for the policymakers and academicians of the health sector.

1. Introduction

Efficiency is the ability of the business to use expertise, technology, and resources to maximize profits and minimize cost. The essential function of any supply chain is to maximize the profit and minimize the cost by optimizing processes. Therefore, supply chain efficiency becomes essential for every business as it is vital to assess the performance of the business. Moreover, it affects the performance of overall business effectively as well. The main objective of this system is to improve the financial strength of the business (Moatti, Ren, Anand, & Dussauge, 2015). It has become crucial for big data to be part of academics and business globally. It is because big data can enable a person to decide within a minute.

Moreover, this decision is more accurate. In this stance, researchers have defined big data analytics as "the amount of data just beyond the capability of the technology to process, manage and store efficiently". Moreover, scholars pointed out that big data is the set of technologies and techniques which need a new kind of integration so the significant values that are hidden can be uncovered. These large values are extracted from the massive-scale data sets, complex and diverse in nature (Özköse, Arı, & Gencer, 2015).

Moreover, scholars pointed out that big data analytics is "the data of which the data volume, acquisition speed, or data representation limits the capacity of using traditional relational methods to conduct effective analysis or the data which may be effectively processed with important horizontal zoom technologies." Therefore, it is important to view big data analytics as a combination of technology and infrastructure that can analyze, store and collect different kinds and types of data (Awan et al., 2021). Furthermore, the additional advantage and value creation are that it has inherited the ability to utilize advanced

techniques for analysis for which it was impossible to process the data through the traditional database (Gangwar, 2020a). Big data has evolved a lot with time since the last few years, practitioners and researchers need to consider how they can integrate the advanced technology adoption. The purpose of adoption is to develop competitiveness for the organizations and firms in the specific industry. The task technology fit plays an important role by investigating the user's requirements for the information to impact the performance. If task technology fits according to the expected performance, it will generate a positive perception (D'Ambra, Wilson, & Akter, 2013).

The first resource category for any organization is infrastructure and tangible resources. Most of the time, the focus of the organizations is on the importance of big data in the form of essential resources to achieve efficiency. To achieve efficiency through data, better database technology is required with good data management. Scholars have pointed out that the effectiveness, as well as efficiency of the firm, can be increased through big data analytics (Sivarajah, Irani, Gupta, & Mahroof, 2020). Supply chain connectivity is one of the important trends to connect different communities economically. It is one of the important and up-to-date trends being followed globally (Alsadi, Alaskar, & Mezghani, 2021). The main objective to develop and adopt an integrated process of the supply chain is to allow the organizations to source different materials throughout the world and have the capability to deliver these materials in any part of the world. In other words, supply chain management involves collaboration and coordination among customers, suppliers, and producers, including third-party service providers. The target of supply chain connectivity is to improve the performance of the supply chain in terms of reducing the uncertainty, cost, and time to move services and goods (Patalinghug, 2015). Understanding the perceived ease of use concept is essential when studying supply chain and connectivity through big data. Perceived ease has the link to how it has become easy to assess the system of technology and display the technology. To accept any system, perceived ease of use plays a vital role. Perceived ease of use is the level to which a person believes that system usage will make him/her free from hard mental effort. Several past studies pointed to the effect of perceived ease of use on the utilization of the system (Abdullah, Ward, & Ahmed, 2016). Therefore, the main objective of this paper is to assess the relationship between Supply chain connectivity, perceived ease of use, task technology fit, big data analytics use, and efficiency of the business in hospitals of Dubai. Moreover, this study also examines the mediating role of big data analytics use among Supply chain connectivity, perceived ease of use, task technology fit, and efficiency underpinned by TAM proposed by Davis (1989).

2. Literature Review

This is the ability to produce or do something without wasting energy, time, and material. Efficiency is also referred to as the degree or quality of being efficient and completing the given task in a limited time. By managing an efficient supply, chain organizations can compete with other organizations effectively and develop a competitive advantage (Bienhaus & Haddud, 2018). Several scholars have mentioned that organizations can gain several financial and operational benefits from efficient supply chain management. Efficiency is the basic concept of management and operationalization of the supply chain that can be key for the organization's success. The focus of efficiency is to minimize waste and improve output. The central facet of supply chain management is to develop the efficient material flow within the organization (Matopoulos, Barros, & van der Vorst, 2015).

Generally, big data is referred to as enormous data sets. Moreover, it becomes challenging for any employee to work on that data using traditional management systems and tools. It also shows that data sets have incredible velocity and variety to generate several new possible solutions to any problem a business may face (Elgendy & Elragal, 2014). Scholars have termed big data as a very big or large set of data that need computational analysis to reveal associations, trends, and patterns related to interactions and human behavior. The scholars also argue that big data must be some difference between big data and traditional data as big data is complicated to handle. Therefore, more sophisticated techniques are required to handle big data (Al-Shiakhli, 2019). Researchers are also opined that new technical tools, analytics, and architectures are required for timeliness, diversity, distribution, and the whole scale to enable insights and unlock new business value resources. The key features of big data are velocity, variety, and volume. Therefore, they are known as the three V's of big data (Vanani & Majidian, 2019).

Big data analytics is the way to get meaningful insights such as customer preferences, market trends, unknown correlations, and hidden patterns. Several different advantages are provided by big data analytics. Organizations can use it to improve their decision-making process, including customer preferences, market trends, and correlations that are not known. There are several advantages of big data, such as improving the decision-making process, preventing fraud, and many others (Hashem et al., 2015). Scholars have defined connectivity of the supply chain as the seamless flow of financial resources, information, and materials through the supply chain that enables two factors, namely physical connectivity and connectivity of information system (Manfred, 2018). Scholars have assessed several factors, including technologies, to improve the organization's supply chain. In the supply chain system, all organizations are involved in meeting the customers' demands. The linkage among the supply chain parties can be direct or indirect. The connectivity of the supply chain facilitates the activities of the supply chain parties. To improve the investment in the global supply chain activities, connectivity is the main requirement (Srimarut & Mekhum, 2020).

Researchers have defined PEOU as the level to which the individuals perceive the ease of using technology. At the same time, perceived usefulness is the level to which a person believes the usefulness of the technology. Scholars argued that PEOU is the level an individual accepts as the proper usage of the whole system (Sugandini et al., 2018). PEOU is the term that a person perceives as innovation, not as complicated and easy to understand, operate and learn. Moreover, a person also perceives that the system is free of the hustle and easy to handle. Ease of use of the system plays a significant role to foreclose the intention of a person, including employees, regarding system usage. When the users have the experience to use any system, it becomes further easy for them to utilize it because they gain confidence regarding system utilization (Ma, Gam, & Banning, 2017). Whereas it is also possible that users of the system might face difficulty using the system properly. Therefore, there must be proper training, awareness programs, and seminars to provide important information whenever a new system is launched. Researchers reported that employees often are not motivated to use the new system. Therefore, they prefer to use the old management system. In this scenario, the organization's management must encourage the employees to use the new system to improve their efficiency and effectiveness (Samuel, Onasanya, & Olumorin, 2018).

TTF is necessary for the business, and it provides a lens towards the usage of technology and creates value for it. In the organization, when employees use technology to perform a set of specific tasks and particular tasks, the performance of the technology is developed through the alignment of required tasks and characteristics of technology due to which a person performs a specific task. The tasks are the totality of cognitive or physical actions and processes done by an individual in a particular environment (Howard & Rose, 2019). The researchers have defined technology as the tools individuals use to execute their tasks. Technology also plays a vital role in assisting the individual in executing tasks. On this basis, TTF is referred to by the researchers as the level to which assistance is provided by the technology to perform a specific task. It is also affected by the interaction among technology functionality and task characteristics (Vanduhe, Nat, & Hasan, 2020).

3. Hypothesis Development

3.1 Supply chain connectivity and Big data analytics use

Organizations can develop big data analytics through the enhancement of the supply chain. Because by this way, the organization will develop connectivity and reach considerable information and large data sets. Which are essential and beneficial for the organization. Scholars have suggested that supply chain connectivity is regarding a firm's IT infrastructure (García, Ramírez-Gallego, Luengo, Benítez, & Herrera, 2016). Moreover, it is a key and essential tangible asset and resource because it can develop big data analytical capability. Organizations develop the ability to deploy, integrate, assemble and access by using big data to enhance the supply chain. Several scholars provide supportive arguments regarding supply chain connectivity rules to enhance knowledge and data sharing capability (Brandon-Jones, Squire, Autry, & Petersen, 2014).

The supply chain connectivity is the critical factor of big data analysis. It provides the ability to develop connections among the employees and the organizations to develop large data sets. It also helps enhance the analytical capability of the individual (Seyedghorban, Tahernejad, Meriton, & Graham, 2020). Therefore, the supply chain's agility and its alignment are ultimately enhanced. The supply chain connectivity is basically regarding the supply chain association with related technology and information. It means connectivity of the supply chain is the firm's ability to quickly use information technology and communication to generate information to reach desired goals (Dubey et al., 2018).

H₁: *SCC is positively affecting BDA.*

H₂: *BDA mediates significantly between SCC and EFY.*

3.2 Perceived ease of use and Big data analytics use

Big data analytics benefit the organization by helping in the decision-making process, controlling risk factors, and cutting costs. Adoption of business development analytics depends upon the consideration of the user in terms of ease of use that the researcher faces while processing large data (Wang et al., 2018). Scholars define PEOU as the level to which users of the technology will be free of effort for an employee or a customer. Past studies indicate that perceived usefulness is positively affected by the PEOU. The technology that a user feels easy to use can be more advantageous. In terms of big data, ease of use makes it easier to analyze more variety and volume of data (Shahbaz, Gao, Zhai, Shahzad, & Hu, 2019; Wu & Chen, 2017). Researchers clarified that ease to use technology and information systems would help to enhance the acceptability of the technology among the users. If the researcher's system is effortless, it will enhance organizational and individual performance. Past studies have mentioned that PEOU has a direct positive relationship with adopting new technology in several different fields (Bauerová & Klepek, 2018). However, it is important to mention that the behavior of users is not much studied in past research regarding the usage of big data in the context of the present study.

H₃: *PEOU is positively affecting BDA.*

H₄: *BDA mediates significantly between PEOU and EFY.*

3.3 Task- technology fit and Big data analytics use

Big data is a large set of data required for the computational analysis to demonstrate the relationships among different variables and behaviors. The scholars also argue that big data must be some difference between big data and traditional data as big data is challenging to handle. Therefore, more sophisticated techniques are required to handle big data (Al-Shiakhli, 2019). Effective information system adoption relies upon identifying different tasks in which technology is to be used. Moreover, there must be a suitable connection between technology and task. Researchers described that TTF investigates the user's requirement regarding a specific information system, which eventually affects that individual's performance (Gangwar, 2020b). The researchers define tasks as the acts that are performed to create value output to satisfy needs and wants. At the same time, technologies are referred to as effective supportive technologies (Dang, Zhang, Brown, & Chen, 2020).

Scholars described tasks as several different factors concerning several technical aspects according to the needs of the individuals. The ability of TTF is significantly affected by the technology and tasks from several different perspectives. If the innovative system cannot fulfill the needs of the individual, then it is a useless system. Thus, it is essential to recognize the significance of big data analytics for organizations (Dang et al., 2020). Past studies discussed TTF in several different aspects to determine the fitness of user tasks for decision-making at the group level and technology. It led to the successful adoption of information systems in different organizations. Thus, based on the above arguments, TTF plays a very important role in developing big data analytics in any organization (Shahbaz et al., 2019).

H₅: *TTF is positively affecting BDA.*

H₆: *BDA mediates significantly between SCA and EFY.*

3.4 Big data analytics use and efficiency

Systems and big data analytics play critical roles in making decisions effectively and efficiently. As a result, the outcomes of business are improved as well. The benefits of using big data can be improved efficiency at the operational level, personalization of the customers, new venture and revenue opportunities, and effective marketing (Shabbir & Gardezi, 2020). Past studies have pointed out that organizations can achieve efficiency and reduce costs by using big data analytics. The resources can be re-configured by using big data analytics so the changes in the demand and supply can be adapted and make forecasts accurately. Moreover, Cheng and Lu (2018) also pointed out that big data analytics plays a significant role in achieving efficiency. Wang et al. (2016) described efficiency as the level to which the buyer saves resources from the supply chain activities with the seller. It also mentions that sharing information has a crucial effect on the efficiency of the buyer. Past studies have acknowledged the importance of big data analytics inefficiency. The application of big data analytics has played a vital role in increasing organizations' revenue. Because of high operational and strategic potential, big data analytics plays a vital role in enhancing the organization's efficiency. High-performing organizations always consider big data analytics for their operations (Koseleva & Ropaite, 2017).

H₇: *BDA is positively affecting EFY.*

4. Underpinning theory

4.1 Technology Acceptance Model

This model is accepted by the technology acceptance model proposed by Davis (1989). The theory proposes that technology plays a vital role in affecting the behavior of a person or organization. This theory shows that subjective norms and attitudes affect how organizations and individuals accept technology (Kamble, Gunasekaran, & Arha, 2019). In this study, supply chain connectivity, PEOU, TTF, and big data usage affect the organization's efficiency.
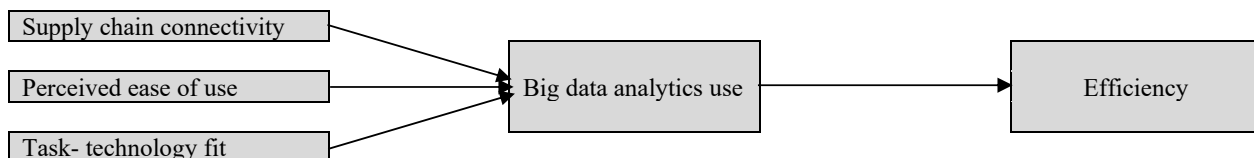

Fig. 1. The proposed study

5. Research Methodology

The scholars of the present study adopted a cross-sectional research design. The current research approach is also quantitative to fulfill the objectives of the present study. Moreover, this research approach was also appropriate for the research design of the present study. The population of the present study was the healthcare sector of the UAE. The data was collected from the employees working in the hospitals of the UAE. All of the hospitals were selected for the present study.

The questionnaire was developed to collect the data from the employees. The questionnaire was developed from past studies. Researchers used the Likert 5 scale for the questionnaire of the present study. In this questionnaire, one represents Strongly disagree, and 5 represents strongly agree. The items of Big Data Analytics Use were adopted from Cheng and Lu (2018), Supply Chain Connectivity Brandon-Jones et al. (2014), task-technology fit scale Shahbaz et al. (2019), Perceived ease of use Shahbaz et al. (2019) Efficiency Cheng and Lu (2018). The developed questionnaire was distributed among 426 employees working in hospitals. The usable questionnaire received back was 312. Thus, the usable response rate of the study was 73.22 percent.

6. Results

The present study performed preliminary analysis before testing the present study's hypothesis. In this preliminary analysis normality of data and missing values were examined. It was found by the researchers that there was no missing value in the present data. Later, At the beginning of the preliminary analysis, the present study tested the variance inflation factor of the data collected. This test is essential to examine the multicollinearity of the data. For this test, Hair, Ringle, and Sarstedt (2012) proposed that the value must be less than 5.0. It is evident from the values of table 1 that values of VIF are less than 5.0.

Table 1
VIF

	BDA	EFY
BDA		1.000
EFY		
PEOU	1.267	
SCC	1.195	
TTF	1.076	

Note: BDA= big data analytics, EFF= Efficiency, SCC= supply chain connectivity, PEOU= perceived ease of use, TTF= technology task fit
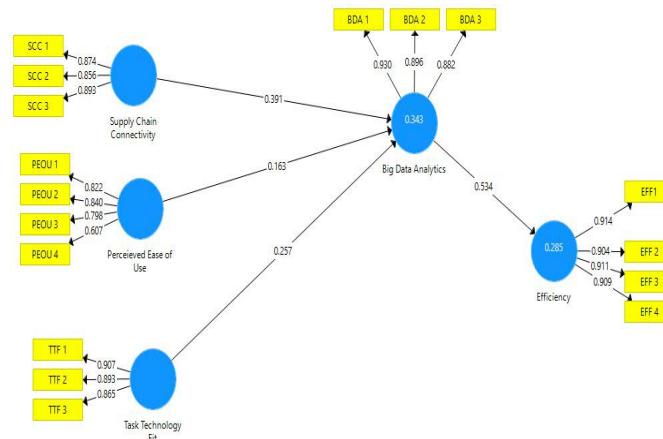

Fig. 2. Measurement Model

Note: BDA= big data analytics, EFF= Efficiency, SCC= supply chain connectivity, PEOU= perceived ease of use, TTF= technology task fit

Thus, the data has proceeded for the measurement model under PLS. For the present data study analysis, PLS 3 was used as the tool to examine the gathered data. PLS was selected because it can test the normal and non-normal data (Reinartz, Haenlein, & Henseler, 2009). Initially, this study assessed the measurement model of the data. The first step of the measurement model was factor loading, as mentioned in Table 2 and Fig. 2. It is evident from the values of factor loading mentioned in table 2 and figure 2 that they are above the benchmark value of 0.50 as proposed by Hair, Celsi, Ortinau, and Bush (2010). Therefore, the items having a value of more than 0.50 were retained as used by past studies (Ali, Azeem, Marri, & Khurram, 2021).

Table 2

Factor Loading

	BDA	EFY	PEOU	SCC	TTF
BDA 1	0.930				
BDA 2	0.896				
BDA 3	0.882				
EFF 2		0.904			
EFF 3		0.911			
EFF 4		0.909			
EFF1		0.914			
PERU 1			0.822		
PERU 2			0.840		
PERU 3			0.798		
PERU 4			0.607		
SCC 1				0.874	
SCC 2				0.856	
SCC 3				0.893	
TTF 1					0.907
TTF 2					0.893
TTF 3					0.865

Note: BDA= big data analytics, EFF= Efficiency, SCC= supply chain connectivity, PEOU= perceived ease of use, TTF= technology task fit

Table 3

The results of the reliability

	Cronbach's Alpha	rho_A	CR	AVE
BDA	0.886	0.887	0.930	0.815
EFY	0.931	0.934	0.950	0.827
PEOU	0.784	0.824	0.854	0.597
SCC	0.849	0.878	0.907	0.765
TTF	0.867	0.867	0.919	0.790

Note: BDA= big data analytics, EFF= Efficiency, SCC= supply chain connectivity, PEOU= perceived ease of use, TTF= technology task fit

The later present study examined the reliability and validity of the data. For this purpose, the value of composite reliability and Cronbach Alpha were gathered, which were more than 0.70 as proposed by Fornell and Larcker (1981) used by Jabeen and Ali (2022). Moreover, it is evident from Table 3 that the value of AVE is more than 0.50, as proposed by Sarstedt, Ringle, Henseler, and Hair (2014). Thus, the present study has achieved discriminant validity.

Table 4

Discriminant validity

	BDA	EFY	PEOU	SCC	TTF
BDA	0.903				
EFY	0.534	0.910			
PEOU	0.389	0.520	0.772		
SCC	0.488	0.456	0.404	0.875	

Note: BDA= big data analytics, EFF= Efficiency, SCC= supply chain connectivity, PEOU= perceived ease of use, TTF= technology task fit

The PLS testing is based on measurement model testing, which is used to examine the data's validity, reliability, convergent validity, and discriminant validity. At the end of the measurement model, discriminant validity of the data is achieved by the square root of AVE, keeping in view the criteria mentioned by Fornell and Larcker (1981). Thus, the measurement model of the present study is assessed. After the measurement model, scholars of the present study examined the proposed hypothesis of the present study. For this purpose, the bootstrapping procedure was adopted.

Table 5

Direct hypothesis

HYP		Beta	SD	T Value	P Values	Decision
H1	**SCC → BDA**	0.391	0.063	6.224	**0.000**	**Supported**
H3	**PEOU → BDA**	0.163	0.062	2.631	**0.004**	**Supported**
H5	**TTF → BDA**	0.257	0.059	4.367	**0.000**	**Supported**
H7	**BDA →EFY**	0.534	0.047	11.287	**0.000**	**Supported**

Note: BDA= big data analytics, EFF= Efficiency, SCC= supply chain connectivity, PEOU= perceived ease of use, TTF= technology task fit

According to values mentioned in Table 5, H1 of the study is also supported with SCA and BDA are statistically significant (Beta=0.391, t value=6.224). Moreover, PEOU and BDA also have a statistically significant relationship with Beta=0.163 and t=2.631, showing H3 to be supported. TTF and BDA are also statistically significant (Beta=0.257, t=4.367), supporting H5.In the end, BDA and EFY are positively associated with each other (Beta =0.534 and t-11.287). Thus, H7 proposed in the present study is statistically significant.

Table 6
In-Direct hypothesis

HYP		Beta	SD	T value	P Values	Decision
H2	TTF → BDA → EFY	0.137	0.035	3.946	0.000	Supported
H4	PEOU → BDA → EFY	0.087	0.036	2.428	0.008	Supported
H6	SCC → BDA → EFY	0.209	0.042	4.983	0.000	Supported

Note: BDA= big data analytics, EFF= Efficiency, SCC= supply chain connectivity, PEOU= perceived ease of use, TTF= technology task fit

The later present study examined the results of mediating results as well. Table 6 shows the results of the mediating hypothesis proposed earlier. According to values given in Table 6, BDA mediates the relationship between TTF and EFY (Beta= 0.137, t=3.946). Moreover, the results confirm the mediating role of BDA among PEOU and EFY (Beta= 0.087, t=2.428), and also mediating effect of BDA is confirmed between SCA and EFY (Beta=0.209, t=4.983). Thus, H2, H4, and H6 are statistically confirmed.

Table 7
R-Square

	Original Sample (O)
BDA	0.343
EFY	0.285

Note: BDA= big data analytics, EFF= efficiency

At the end of the structural model, the present study also examined the value of R square. The value of R square shows the effect of IV's on the DV of the study. According to the value mentioned in Table 7, both values of R square are more than 0.19, as proposed by Chin (1998). Below is a given structural model of analysis.
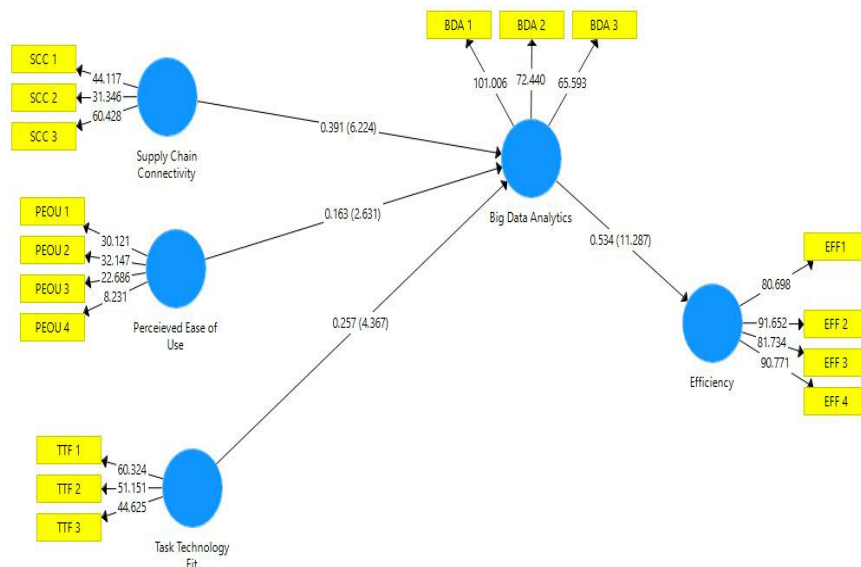
Note: BDA= big data analytics, EFF= Efficiency, SCC= supply chain connectivity, PEOU= perceived ease of use, TTF= technology task fit

Fig. 3. Structural Model

7. Discussion

This study was conducted to examine the effect of supply chain connectivity, perceived ease of use, and technology task fit on big data analytics and efficiency of the health care sector of UAE. This study was conducted to find the effect of different factors that can improve the efficiency of the health care sector in the UAE. The study found that Supply chain connectivity is very important for the acceptance of big data analytics in healthcare. These results were in line with the findings of (Brandon-Jones et al., 2014). Moreover, the study's findings also confirmed that usage of big data could play a significant role in improving their efficiency. With the help of big data, they can assess the trend and behavior of the patients. They can also

record the proper feedback of the patients. Thus, their efficiency will be improved. This result is similar to the results of (Koseleva & Ropaite, 2017).

The present research also confirms that PEOU has a significant positive relationship with big data analytics. The study's findings also confirmed that PEOU is very important for the adoption of big data within the organization. If the employees feel easy using the system, they will adopt the change and new technology quickly. If users feel at ease using a specific technology, they will prefer to use it. The study's findings are in line with the findings of (Wang et al., 2018) regarding the relationship between perceived ease of use and big data analytics use. The research outcomes demonstrate that TTF has an essential role in significant data adoption. The research also proves that if task technology fits within the organization, the decision-makers will quickly adopt big data within the firm. Thus, the hospital management must try to develop TTF within their organizations. These findings align with the findings of (Shahbaz et al., 2019), which illustrates a clear and distinctive relationship of the task- technology fit with big data analytics use.

Additionally, the adoption of business development analytics depends on the consideration of the user in terms of ease of use that the researcher faces while processing extensive data. Hence, these study findings are in-line with the findings of (G. Wang et al., 2016). The study's findings also confirm the mediating role of big data analytics.

8. Conclusion and Implications

This research was conducted to examine IT-related factors' role in achieving efficiency in the health sector. This study found that big data analytics must be the decision-makers focus to achieve efficiency in their operations. It is because big data plays a very important role in securing the data. As a result, work will be conducted efficiently and effectively. On the other hand, the usage of the system is also dependent upon its user-friendliness. If it is easy to use, users will prefer to adopt big data. This research also provides insight into the importance of supply chain connectivity. Different departments of the organization must be linked to each other to share resources and information required to complete the operations. Furthermore, the tasks assigned to the employees must handle the tasks. They must have the skills to handle the situation.

This study fills several theoretical and managerial gaps. The proposed model of the study was successfully explained through TAM through the mediation of big data analytics so organizations can achieve efficiency through the usage of SEM. This study fills the gap of the scarcity of studies regarding limited studies conducted for big data in the health sector. Moreover, this study also fills the gap of limited studies on the mediating role of big data in management research. Like any empirical study, there exist a few limitations. This study has adopted a cross-sectional approach, whereas future research can use a longitudinal approach. The study's findings are helpful for the managers and academicians of the healthcare sector.

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