The Impact of Technology Readiness on the Big Data Adoption Among UAE Organisations

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Abstract Big Data is an important player in offering a highly competitive advantage, specialty, in contemporary organisations. The theory of technology readiness can be used for measuring the readiness of an organisation to adapt big data. Structural equation modelling is used in this study through AMOS to analyse 381 valid questionnaires to evaluate the proposed model built on the Theory of Technology Readiness to determine the factors that could affect big data adoption. This research concentrates on one of Abu Dhabi's public organisations (ADPO). In this model, the key independent constructs are comparable to Innovativeness, Optimism, Insecurity and Discomfort pertaining to these organisations' readiness for exploiting this massive data amounts. The dependent constructs are based on the adopted big data's readiness in ADPO. The relations between the different constructs are defined in this research. This work has enhanced our insights regarding the online social networking model. The results showed that all four independent variables considerably helped to predict the adoption of big data with different percentages. The model that was put forward explained 50% of the variance occurring in the adoption of big data.

Keywords Optimism · Innovativeness · Discomfort and insecurity · Big data · Adopting · Theory of technology readiness · Public sector · UAE

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1 Introduction

In a contemporary organisation, *Big Data* is an important player in offering a highly competitive advantage. Most organisations try to benefit because it provides a deeper understanding of its customers and their requirements. This helps to make appropriate and appropriate decisions within the company in a more effective manner based on information extracted from customer databases [1, 2]. Specialised IT research and consultancy defines big data as a large, fast-flowing and highly diversified information asset that requires cost-effective and innovative processing methods to develop insights and decision-making. It is also defined by the company (IBM); Big Data is created by everything around us. At all times, every digital process and every exchange in social media produces huge data, transmitted by systems, sensors, and mobile devices. Big data has multiple sources of speed, size and diversity, and to derive significant benefit from large data. "We need perfect treatment, analytical abilities, and skills" he said. The International Standards Organization (ISO) has defined big data as groups or sets of data with unique characteristics (e.g. size, speed, diversity, variability, data health, etc.), which cannot be efficiently addressed using current and traditional technology to make use of it.

Big data was defined by the International Telecommunication Union (ITU) as data sets that are super-large, fast, or versatile, compared to other types of data sets used. Speed is a crucial factor in decision-making based on these data; which is the time it takes from the moment these data arrive to when the decision is made. Previously, companies used to process small sets of data stored in a structured data image in a process database, where each dataset was analysed one by one pending the arrival of the results. Big data is an important player in offering a highly competitive advantage, specialty, in contemporary organisations. Most organisations seek it for benefits since it gives a deeper understanding regarding the customers as well as their requirements. This research will insight the impact of technology readiness on big data adoption among public organisations in Abu Dhabi, UAE.

2 The Status of Big Data Technology in the UAE

The United Arab Emirates (UAE) started adopting large-scale data technology since 2013. Establishment of a smart government was the first application, which was aimed at providing services to the UAE public around the clock, anywhere. The goal of this project is to take advantage of the huge data applications to serve the UAE citizens around the clock and anywhere in the world [3]. The idea of this project was based on the context of the Government's efforts to develop government services and achieve high quality of life for UAE citizen and residents, according to the UAE Vision 2021 [4–6].

As part of its efforts to implement the Smart Government Initiative, the AE General Authority for Development has prepared the Smart Government Roadmap, which provides a plan for the UAE to move from e-government to smart government. The map sets out a range of tasks covering the period until 2015. The scope of the road map is in line with the current federal e-government strategy 2012–2014, with emphasis on environmental improvements, enhanced user readiness and user satisfaction [7, 8].

The United Arab Emirates plans to set up Dubai Smart City in cooperation with Emirates Integrated Telecommunications Corporation. The first phase of the Dubai Smart Platform, is an interactive database that allows residents, visitors and institutions to analyse data and information that is electronically collected and collected from local government institutions to achieve the concept of satisfaction and the happiness of users. Dubai's artificial intelligence road map, Dubai Smart, in partnership with a network of private and public partners, strives to search for innovative technology solutions to enhance the quality of life in Dubai as well as make the city more efficient, safe, smooth and effective in terms of experience.

UAE government has identified areas of focus within four parallel tracks, which correspond to the Smart government, which are:

- Creating a general environment in which the smart government thrives
- Assess the capabilities of government agencies
- Establish joint resources through government agencies at a national level
- Happy citizens.

In the UAE, different entities must discuss artificial intelligence as well as the capability that allows understanding natural language, verifying and analysing large databases swiftly, and reach conclusions based on transactions, as well as recommend relevant information to aid users in selecting appropriate next steps. To install on a platform, a smart window will be created to collect the services it needs daily, which can be changed at any time, thus minimising this concept. The government's ability is considerably improved with the platform in making quick decisions with the available data, which allows city leaders to get involved in community-wide dialogues and evaluate rich city data across numerous dimensions. The platform enables additional improvement for the existing smart initiatives and services based on analysis as well as data-based innovation.

3 Literature Review

3.1 The Optimism

The identification of optimism lies with the inclination to have "a constructive view regarding innovation as well as a conviction promising to give individuals expanded control, proficiency and adaptability in their lives" [9]. Self-assured individuals are suggested to embrace innovation, and in evaluation, to various buyers, are less likely be inclined to centre on the contrary parts associated with inevitable hardships as well as disappointments in new advancements, should they occur (Kotler & Armstrong). Since innovation is seen by confident people with a perspective of conceivable outcomes, it could also be expected that hopeful purchasers may see self-scanners as both less demanding and more valuable for use versus non-idealistic buyers.

There are many studies that have shown a positive connection between big data adoption BDA and optimism. In one of the key examinations regarding BDAs, Dabholkar (1996) found that a higher level of control was permitted to the shopper, for touch-screen request in the cost-effective food industry. The impression of purchaser control has also been seen to be emphatic with the purchaser acknowledging shopper in self-requesting booths that can be found in eateries (in the same place), as well as self-registration stands at air terminals. These discoveries were in line with the findings of Dabholkar et al. (2003), who discovered self-filtering DDAs, that control and efficiency are also the major determinants for the buyer acknowledgment of BDAs. Thus, the below hypothesis is proposed:

H1: Optimism has a positive impact on big data adoption.

3.2 The Innovativeness

The identification of creativity lies with the inclination "towards being a thought pioneer and an innovation pioneer" [9], in which the creative buyer is guessed to be bold in employing innovation. Furthermore, inventive purchasers are guessed to view innovation as being simple, since they possess an abnormal state of mechanical information, as well as a certifiable enthusiasm to detect new innovation [9]. As creative purchasers perceive innovation as being interesting, it can be highly expected that imaginative customers perceive self-scanners as being more significant and less demanding to employ than others.

As opposed to the other TR-ideas, it seems that contemporary BDA researchers have not explored Innovativeness fairly. Likewise, for some of the examinations conveyed, addressing of (i) the unwavering quality of the measure, as well as (ii) the beneficial outcome has been done, as proposed by the TR-writing. In fact, experimental studies have confirmed that an absence of viability in the Innovativeness measure continues to persist by all accounts, mainly since the distinction between general innovativeness and area particular cannot be thought with the measure. Beyond a doubt, the space particular Innovativeness has been put forward as being firmly identified with the selection of innovation, while as a frail indicator to innovation acknowledgment, the general Innovativeness has been put forward. Liljander et al. (in the same place) found that the Innovativeness measure can be enhanced as a positive measure regardless of its general methodology, a measure that could possibly contribute to the aggregate informative degree. Be that as it may, the feedback for Innovativeness measure is considered to be more grounded. In this, specifically, a sharp feedback was coordinated by Roehrich (2004), and it concentrated on a non-substantial indicator to acknowledge innovation. Due to this insightful concern, as of late, the innovation preparation record was streamlined by Parasuraman & Colby [9] who re-assessed the measure. Post the re-assessment, it was found that the measures' unwavering legitimacy and quality was of a solid help. Thus, the below hypothesis is proposed:

H2: Innovativeness has a positive impact on big data adoption.

3.3 The Discomfort

Uneasiness identifies with the inclination to have an "apparent absence of command over innovation and a sentiment of being overpowered by it" [9]. Purchasers that have a mechanical Discomfort were predicted to possess a sense of general distrustfulness towards innovative tension, development and changes, technophobia [9] and a general negative perception when linking with new or outsider innovation.

With the absence of saw value as well as saw usability for a specific innovation, the BDA writing has risen to Discomfort. Here, Kallweit et al. (2014) evaluated self-benefit data and observed advancements in terms of a reduction in saw usability that casts a critical negative effect on the adequacy of the client; hence, it appears that Discomfort and purchaser acknowledgment of BDAs possess a negative relationship. This end, however, is not questionable. Meuter et al. (2003), emphatically underscore that distress, for example, innovation nervousness, is a conceivable motivation to why customers maintain a strategic distance from innovation. Hence, at the end of the day, force a negative connection among inconvenience and the utilisation of innovation. Thus, the below hypothesis is proposed:

H3: Discomfort has a negative impact on big data adoption.

3.4 The Insecurity

Weakness identifies with the propensity to have "doubt of innovation and distrust about its capacity to work appropriately" [9]. Once in a while, shoppers with Insecurity are ready to rely on innovation. They believe that innovation comes up short during the most basic minute [9]. Accordingly, purchasers with Insecurity have been linked to both equivocalness as well as a general low utilisation of innovation. For sure, as emphasised by both Kotler and Armstrong (2012) and Parasuraman and Colby [9], customers with Insecurity are sometimes a buyer that embraces innovation enthusiastically, yet they do it when there is no more decision. With these, it can be accepted that self-scanners are observed by shaky buyers as both harder and less valuable for usability versus different purchasers.

For instance, with regards to the Innovativeness measure, unique effects were discovered by researchers which concern Insecurity. For example, Godoe and Johansen

(2012) and Walczuch et al. (2007) confirmed that the identification of Insecurity is not fundamental along with a negative assessment for the saw handiness. In spite of what could be expected, "one could expect that individuals will realise fundamental estimation for a framework that pays little heed to how things are being handled". In line with this thinking, Gelderman et al. (2011) contended that there is low effect of Insecurity, yet basically considered the measure to be inconsistent and frail. However, rather than stressing its small size, they imply that insecurity is a negative idea; yet, because of its shortcomings, should be joined with the more grounded proportion of Discomfort. Notwithstanding, in the on-going TR re-assessment, Parasuraman and Colby [9] found that Insecurity is without a doubt emphatically identified with absence of trust in innovation, from one viewpoint, and a lower inclination to utilise innovation, then again; therefore, forcing a negative connection among Insecurity and the general acknowledgment of advances. Thus, the below hypothesis is proposed:

H4: Insecurity has a negative impact on big data adoption.

4 Research Methodology

4.1 Proposed Conceptual Framework

In the conceptual framework, the hypothesised relationships between the constructs have been taken from the relevant literature. Figure 1 displays the put forward model with optimism, discomfort, innovation and insecurity to forecast the adoption of big data. These relationships are taken from [9]. The said model examines the relationship between the constructs among employees in the public organisations of Abu Dhabi in the UAE. Four hypotheses are tested with the suggested conceptual framework.

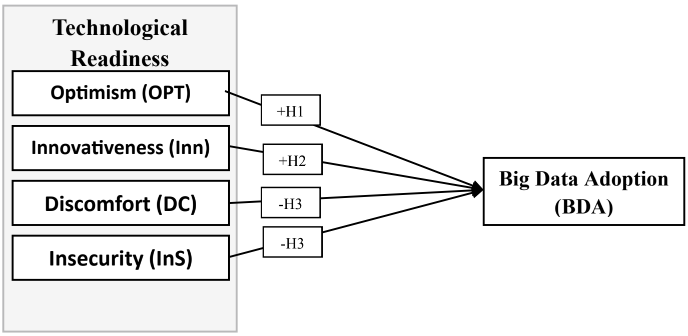

Fig. 1 Proposed conceptual framework

4.2 Research Instruments

A 17-item questionnaire was used to construct the instrument for this study and a multi-item Likert scale was also applied as per the information systems in the literature [10]. A Likert scale was employed to measure the constructs, which was recommended in the earlier studies [11, 12], in which 5 referred to 'Strongly Agree' and 1 to 'Strongly Disagree'. Since the respondents were Arabic speakers, translation of the questionnaires from English to Arabic was done in a precise manner. Thus, a back translation was also employed, which is an approach employed broadly in cross-cultural surveys [13–15]. In this study, the measurement of the variables was validated by employing extant research. For each construct, the number of items was determined based on the guidelines of Hayduk and Littvay (2012) who advocated to employ few optimal items.

4.3 Data Collection

To employees within the public sector in the UAE, self-administered questionnaires were delivered personally from February to July 2018 for data collection. Out of the total of 550 distributed questionnaires, 403 were returned; for the analysis, 381 were considered appropriate. The sample size was adequate as per Krejcie and Morgan [16] and Tabachnick and Fidell [17]. In comparison to relevant literature, this study's 69.27% response rate was considered to be highly satisfactory [18]. There were a total of 33 excluded questionnaires, including 12 cases that had missing data for more than 18% of the questions, 11 cases with straight lining and 5 cases as outliers.

5 Data Analysis and Results

For this study, structural equation modelling (SEM) was selected as an analytical technique since it allows simultaneous analysis to get enhanced accurate estimates [13, 14, 19–22].

5.1 Measurement Model Assessment and Confirmatory Factor Analysis (CFA)

The indices of goodness can be seen in Fig. 2. The SEM software is implemented practically here. Table 1 shows the acceptable outcomes as per the earlier studies. On the basis of Table 1 and Fig. 2, all indices representing *goodness-of-fit* exceeded levels

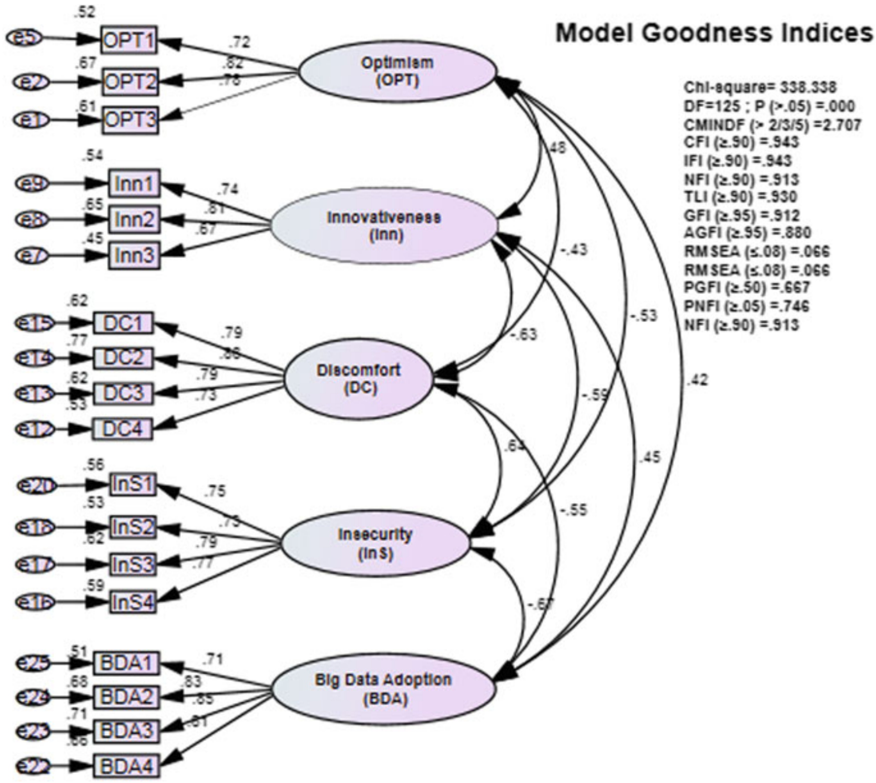

Fig. 2 Result of confirmatory factor analysis (CFA)

of acceptance as suggested by the earlier research, thus pointing out that the model of measurement exhibited a good fit compared to the gathered data. The indices representing the total fit show that the chi-square is insignificant (*p*-value should be >0.5). In spite of the insignificant chi-square, the prototype still fits since the chi-square value almost always discounts the prototype when sizeable samples are considered [23]. The fact that the chi-square is responsive for a sample size of greater than 200 is noteworthy [24], and the size of the sample for this research is 381. Thus, we can proceed to assess the psychometric attributes of the measurement prototype in terms of indicator and construct reliability, and discriminant and convergent validities.

As far as the construct reliability is concerned, the findings indicate that each of the individual alpha coefficient of Cronbach are greater than the recommended level of 0.7 [25]. Moreover, in evaluating construct reliability, all CR (composite reliability) values were larger than the suggested value of 0.7 [26, 27]. This conclusion corroborates that there has been achievement of construct reliability (Table 2). To find out indicator reliability, loadings of factor were examined [28]. The loading for every article surpassed the advised value 0.5, and hence the loadings for each article are fulfilled not counting article OPT4 and article Inn4, which had been removed due

Table 1 Goodness-of-fit indices for the measurement model

Fit index	References	Admissibility	Result	Fit (Yes/No)
X^2			338.338	
DF			125	
p-value		>0.05	0.000	No
X^2/DF	[27]	1.00–5.00	**2.707**	**Yes**
RMSEA	[39]	<0.08	**0.066**	**Yes**
SRMR	[40]	<0.08	0.066	Yes
GFI	[41]	>0.90	0.919	Yes
AGFI	[41]	>0.80	0.880	Yes
NFI	[23]	>0.80	0.913	Yes
PNFI	[23]	>0.05	0.746	Yes
IFI	[42]	>0.90	0.943	Yes
TLI	[43]	>0.90	0.930	Yes
CFI	[24]	>0.90	**0.943**	**Yes**
PGFI	[44]	>0.50	0.746	Yes

The indexes in bold are recommended because they are frequently reported in the literature [45]
Note X^2 Chi Square; *DF* Degree of freedom; *CFI* Comparative-fit-index; *RMSEA* Root mean square error of approximation; *SRMR* Standardized root mean square residual; *GFI* Goodness-of-fit; *NFI* Normed fit index; *AGFI* Adjusted goodness of fit index; *IFI* Increment fit index; *TLI* Tucker–Lewis coefficient index; *PNFI* Parsimony normed fit index

to low loading. Also, in order to observe convergent validity, AVE (average variance extracted) was utilised, and all values of AVE were bigger than the recommended value 0.50 [29]. Thus, adequate convergent validity was exhibited successfully. As far as the construct reliability is concerned, the findings indicate that each of the individual alpha coefficient of Cronbach is greater than the recommended level of 0.7 [25]. Moreover, in evaluating construct reliability, all CR (composite reliability) values were larger than the suggested value of 0.7 [26, 27]. This conclusion corroborates that there has been achievement of construct reliability (Table 3). To find out indicator reliability, loadings of factor were examined [28]. The loading for every article surpassed the advised value 0.5, and hence the loadings for each article are fulfilled not counting article OPT4 and article Inn4, which had been removed due to low loading. Also, in order to observe convergent validity, AVE (average variance extracted) was utilised, and all values of AVE were bigger than the recommended value 0.50 [29]. Thus, adequate convergent validity was exhibited successfully.

Table 2 Measurement assessment

Constructs	Item	Loading (>0.5)	*M*	SD	α (>0.7)	CR (>0.7)	AVE (>0.5)
Optimism (OPT)	OPT1	0.718	3.405	1.025	0.914	0.82	0.60
	OPT2	0.819					
	OPT3	0.778					
Innovativeness (Inn)	Inn1	0.737	3.395	1.037	0.914	0.78	0.55
	Inn2	0.808					
	Inn3	0.668					
Discomfort (DC)	DC1	0.788	3.259	0.996	0.903	0.84	0.64
	DC2	0.877					
	DC3	0.787					
	DC4	0.731					
Insecurity (InS)	InS1	0.737	3.333	1.091	0.927	0.78	0.55
	InS2	0.808					
	InS3	0.668					
Big data adoption (BDA)	BDA1	0.711	3.201	0.969	0.886	0.87	0.64
	BDA2	0.826					
	BDA3	0.846					
	BDA3	0.813					

Key OPT Optimism; *Inn* Innovations; *DC* Discomfort; *InS* Insecurity; *BDA* Big data adoption
Note M Mean; *SD* Standard deviation; *AVE* Average variance extracted; *CR* Composite reliability; α Cronbach's alpha

Table 3 Discriminant validity assessment

	Factors	1	2	3	4	3
		InS	OPT	Inn	DC	BDA
1	InS	**0.894**				
2	OPT	0.731	**0.894**			
3	Inn	0.712	0.605	**0.874**		
4	DC	0.774	0.611	0.631	**0.848**	
5	BDA	0.667	0.655	0.511	0.611	**0.865**

Note Diagonals represent the square root of the average variance extracted while the other entries represent the correlations
Key OPT Optimism; *Inn* Innovations; *DC* Discomfort; *InS* Insecurity; *BDA* Big data adoption

5.2 Structural Model Assessment

The structural prototype's goodness-of-fit can be compared to the earlier model for CFA measurement. In the case of this structural prototype, the values were documented as CFI = 0.943, $X^2/df = 2.707$, and RMSEA = 0.066. These indices of fit point out to the acceptable fit amid the theorised model and experimental data [24]. Therefore, the structural prototype's path coefficients can now be investigated.

5.2.1 Direct Hypotheses Tests

The conjectures of this research were verified by employing SEM through AMOS (Fig. 3). The structural prototype assessment displayed in Table 4 gives indication of the experiments on the theories, with all the 4 theories of this research being backed

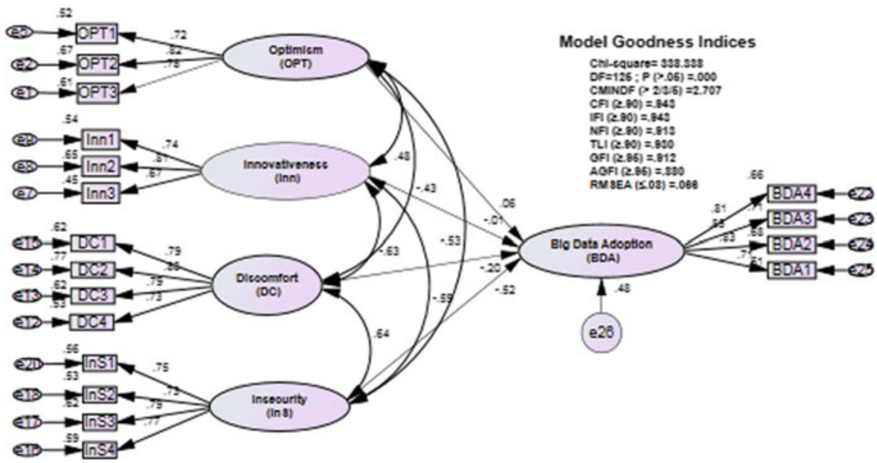

Fig. 3 Structural model results

Table 4 Structural path analysis results

Hypothesis	Dependent variables		Independent variables	Estimate *B* (path coefficient)	S.E	C.R (*t*-value)	*p*-value	Decision
H1	BDA	<—	OPT	0.48	0.039	2.331	0.004	Supported
H2	BDA	<—	Inn	**0.53**	0.042	2.011	0.022	Supported
H3	BDA	<—	DC	0.20	0.042	2.033	0.011	Supported
H4	BDA	<—	InS	0.52	0.035	2.422	0.017	Supported

S.E Standard error; *C.R* Critical ratio
Key OPT Optimism; *Inn* Innovations; *DC* Discomfort; *InS* Insecurity; *BDA* Big data adoption

Table 5 Coefficient of determination result R^2

Exogenous construct	Endogenous construct	R^2	Cohen [46]	Chin [47, 48]	Hair et al. (2013)
OPT, Inn, DC, and InS	BDA	0.48	Substantial	Moderate	Moderate

Key OPT Optimism; *Inn* Innovations; *DC* Discomfort; *InS* Insecurity; *BDA* Big data adoption

up by optimism ($\beta = 0.48$, $p < 0.05$), discomfort ($\beta = 0.20$, $p < 0.05$), innovations ($\beta = 0.53$, $p < 0.05$), and insecurity ($\beta = 0.52$, $p < 0.05$) factors, all having an affirmative effect on the big data. Thus, H1, H2, H3, as well as H4 are encouraged. Observe that the coefficient of the standardised path point out to the strengths of the correlation between dependent and independent variables, and so the explicit effects of the factor of innovation on big data acceptance of ADPO are more solid compared to other independent variables.

5.2.2 Coefficient of Determination R^2: The Variance Explained

The structural model R^2 value showed that all R^2 values are adequately high in order that the prototype can fulfil a reasonable amount of explanatory power [30] (see Table 5).

6 Discussion

Using the suggested prototype, this research provides an improved insight into the role played by the theory attributes such as the readiness of technology as well as other similar aspects in terms of actuality which have a direct effect of embracing big data for providing conditions in estimating the acceptance of big data among the staff members in Abu Dhabi and stresses the relevant consequences. The analyses are given further as follows.

The research discovered that optimism parameter has an affirmative effect on the ADPO adoption of big data among participants, and this result is supported by earlier studies [31, 32]. This result can be justified by the fact that more positivity is useful for enhancements in inspiring the organisation to use few resources on big data depending on their financial situation and to get equipped with the most recent technology for competitive advantage.

Similarly, the innovation certainly affects ADPO adoption of big data among participants, and this result is supported by the earlier studies [32–34]. This result is explained by the fact that increase assisting organisation for turning to the big data system for supporting process available for big data adoption through providing most of the necessary help and resources to enable people to use big data application.

Moreover, the discomfort factor was discovered to have an optimistic effect on the ADPO adoption of big data among participants, and this result is backed up by earlier studies [33]. This outcome can be justified on the basis of the reality that it is uncomfortable when there is trouble related to the big data technology while it is being watched by the people and also when that application is not easy to use. Certain conclusive results from big data are difficult to comprehend.

At last, the factor of insecurity was proved to have an affirmative effect on the ADPO adoption of big data among participants, and this result is supported by the earlier research [35–37]. The justification for this result can be given by the fact that the constructed inputs raise insecurity in the adoption of big data and decrease the self confidence in the use of big data system by having validations and security concerns.

7 Implications, Limitations and Future Directions

The theory of the readiness technology (TRD) has played a vital role in understanding what affects the acceptance and adoption of different types of technology applications of big data as a main part of ionisation successes. This work successfully validates TRD in a new context, namely, in the usage of ADPO among employees in a public organisation in the UAE.

This study has inferences for better understanding of the relations among the different significant aspects concerned with the big data technology adoption in a public organisation. The findings should be relevant to researchers, policy makers, and industry players. Given the trend and status of big data and ADPO, it seems probable that they are able to promote UAE in general and in particular Abu Dhabi to appeal to visitors from the entire globe. Thus, the Abu Dhabi tourism agency and policy makers of the government are directed to integrate the adoption of big data into their operational procedures. These positive opinions are also documented in the literature [38]. This research is limited to only a single public sector organisation of the UAE, and so its findings should be considered with caution.

8 Conclusion

Big Data is an important player in offering a highly competitive advantage, specialty, in contemporary organisations. This study has inferences for better understanding of the relations among the different significant aspects concerned with the big data technology adoption in a public organisation. The findings should be relevant to researchers, policy makers, and industry players. Given the trend and status of big data and ADPO, it seems probable that they are able to promote UAE in general and in particular Abu Dhabi to appeal to visitors from the entire globe. Thus, the Abu Dhabi tourism agency and policy makers of the government are directed to integrate the adoption of big data into their operational procedures. These positive opinions are also documented in the literature [38]. This research is limited to only a single public sector organisation of the UAE, and so its findings should be considered with caution.

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