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Understanding Big Data Adoption and its Impact on Decision-Making Quality: A Perspective from Public Sector IT Managers in Oman

Ghalib AlGhafri, Taiseera AlBalushi, Md Mahbubur Rahim

Department of Information Systems, Sultan Qaboos University, Sultanate of Oman

S132430@student.squ.edu.om, taisira@squ.edu.om (corresponding author), r.mahbubur@squ.edu.om

Abstract. This study investigates the impact of digital transformation and substantial data generation, commonly referred to as big data, on decision-making quality within Oman's public sector organizations. The widespread use of disruptive digital technologies has led to a significant influx of data, aiming to enhance economic, environmental, and social performance. Recognizing the inherent limitations of data alone, organizations are prioritizing investments in data analytics to facilitate informed decision-making and elevate overall performance. To achieve the study's objectives, a two-stage mixed-methods approach was employed. Initially, a systematic literature review was conducted to identify factors influencing adoption of Big Data Analytics (BDA). Subsequently, in the second stage, a questionnaire was administered to assess the impact of these factors on BDA technology adoption and its role in decision-making making within the IT departments of public organizations in Oman, utilizing a cross-sectional research strategy. Partial Least Squares Structural Equation Modeling was employed to uncover significant factors influencing the adoption of BDA and its subsequent impact on decision-making quality. The findings indicate that relative advantage, complexity, and insecurity significantly predict technological considerations. At the organizational level, top management support and readiness emerge as substantial predictors. Additionally, competitive pressure and government regulations are identified as significant environmental components influencing BDA adoption. In conclusion, the study demonstrates that BDA can effectively enhance decision-making quality in public sector organizations, providing valuable insights for both practitioners and scholars in the ongoing discourse on digital transformation and data-driven decision-making quality. The study employs the Technological Organizational Environment theory to assess the practical impact of selected factors. Data were collected from 332 IT professionals engaged in decision-

Keywords: Big data analytics (BDA), Systematic Literature Review (SLR), Technology adoption, TOE theory, Decision-making quality, Public sector organizations

1. Introduction

Data has a huge impact on gaining new knowledge, stimulating corporate innovation, and gaining competitive advantage in the face of the continuous expansion of Industry 4.0 (Nasrollahi et al., 2021). Following disruptive developments (digital transformation) of Industry 4.0, the availability of data has increased exponentially, resulting in an increase in the volume, variety, and speed of data available (Wilkin et al., 2020). The 2019 E-government Development Index (EGDI) survey by the United Nations Department of Economic and Social Affairs (UN DESA) identified the United Arab Emirates (UAE) as the twenty-first nation with a high EGDI. Along with Bahrain, Saudi Arabia, Kuwait, Oman, and Qatar, the UAE is a member of the Gulf Cooperation Council (GCC), which collectively achieved an impressive ranking of V3, indicating the second-highest rank within 'Very High EGDI' (El Khatib et al., 2022). How this big data is creating value for public and private sector organizations is dependent on the absorption and application of big data analytics (BDA) into strategic and operational activities (Amin et al., 2023). In the public sector, for instance, BDA enables insight into the interaction of government programs; it guides effective program performance (Al-Malahmeh, 2022), efficient government operations, and improved quality of life in areas ranging from child welfare and public health to fighting prescription abuse and improving the education sector (SAS, 2017).

The term "big data" appeared for the first time in 2005, meaning a collection of data whose bulk makes it almost impossible to manage or process utilizing traditional business intelligence instruments. However the BDA revolution has made it possible for organizations to analyze such data and gain insights from it (Kartal, 2021). BDA is the use of mathematics and algorithms to extract knowledge from big data in order to enhance the decision-making abilities of practitioners and policy makers (Jeble et al., 2017; Shi, 2022). The success of BDA initiatives is reliant on the quality of decisions that it enables organizations to make. According to Raghunathan (1999), decision-making quality refers to the precision and accuracy of decisions. The quality of decisions can either improve or deteriorate as the quality of information and its processing improves (Raghunathan, 1999). As the size, complexity, and incomprehensibility of data increase, humans' limited cognitive abilities make it difficult to decode and interpret an unfamiliar environment (Sammut & Sartawi, 2012).

Businesses and industries have realized the impact of BDA and started implementing some strategies for big data adoption to gain competitive advantages. In spite of the benefits of BDA in many areas and sectors, there is little information available about the effective operationalization of BDA in business problem-solving or decision-making (Akter et al., 2019; Elgendy & Elragal, 2016; Polese et al., 2019). In particular, the public sector remains a few steps behind (Coulthart & Riccucci, 2022; Microstrategy, 2020). The absence of BDA cab jeopardize decision-making and hamper organizations from taking advantage of market opportunities, consequently compromising the capacity to create value (Walker & Brown, 2019). In the case of Oman, the country adheres to its Vision 2040 plan which aims to integrate global technology, innovation, and industrial revolution trends into national plans to ensure the transition to an economy based on knowledge, innovation, and technology (Oman's Vision 2040, 2021).

The Ministry of Transport, Communication, and Information Technology has implemented an open data initiatives project to promote the sharing of data by government entities, companies with at least 25% government ownership, and companies involved in public services. The objective is to make this data accessible for global reuse and, more importantly, to drive Oman's transition into a knowledge-based society during the Fourth Industrial Revolution (4IR) era (MTCIT, 2021). This will lead to many benefits for organizations that use BDA solutions to their advantage. Various surveys indicate that government organizations are just beginning to embrace big data, lagging behind the private sector (Coulthart & Riccucci, 2022; Microstrategy, 2020). Although these organizations collect substantial data, integration into their daily operations is lacking. More rigorous studies are necessary to understand BDA adoption factors and their impact on decision-making quality. Despite its importance in decision-making, there is a shortage of studies on the role of big data (Janssen et al., 2017). BDA can be effective in empowering the public sector by enhancing current procedures and utilizing analytical techniques that have never been used before (Mittal, 2020). It can also increase the sector's efficiency, effectiveness, productivity, and transparency (Ukhalkar, 2020; Zarina Abdul Jabar et al., 2022). Yet, the meaning and context of data in big data (BD) might not always be fully grasped, affecting decision quality due to a limited understanding of BD sources (Kartal, 2021). Despite the advantages of BDA across various fields, there is limited knowledge about its effective use in solving business problems or making decisions (Akter et al., 2019; Elgendy & Elragal, 2016; Polese et al., 2019). Thus, even with the powers and various benefits of BDA, the public sector in Oman remains worried and uncertain about its readiness to adopt BDA and if it is fully equipped to employ these methods (Hashimiyah, 2019).

In addition, inconclusive findings have been found in many previous studies on the influence of big data analytics on decision-making quality (Shamim et al., 2020). For instance, some have found that the adoption of BDA leads to an improvement in decision-making quality (Shamim et al., 2019), while contrasting findings have been reported by others (Ghasemaghaei & Turel, 2021). Moreover, junior employees may possess a more sophisticated or advanced understanding than their superiors, and institutional processes may need time for the transfer of essential knowledge and skills to senior managers (decision-makers) (Pugna et al., 2022). Some scholars have suggested that to comprehend the determinants of BDA adoption and its impact on decision-making, an understanding of the standpoint of employees at the operational level (such as IT professionals) would give more refined conclusions (Baig et al., 2021; Ghasemaghaei et al., 2018; Pugna et al., 2022; Thirathon et al., 2017; Wilkin et al., 2020). Accordingly, this study examines how IT professionals adopt BDA to enhance decision-making quality. Due to the extensive use of multi-source data from diverse datasets in BDA, IT professionals are the best qualified to provide recommendations in this area. Therefore, the motivation behind this study is to uncover the factors influencing Big Data Analytics (BDA) adoption in the public sector through a systematic literature review (SLR) and assess the impact of BDA on the quality of decision-making as seen by IT professionals in Oman. The study has two main objectives:

- To understand big data, characteristics and techniques, and discover the determinants of BDA adoption and their level of significance from the perspectives of IT professionals in the context of the public sector in Oman.
- To assess the impact of BDA on the quality of decision-making in the public sector in Oman.

The following section of this paper reviews related literature and develops a conceptual model. Next, the methodology section explains the research strategy, data collection and analysis techniques used in this study. After this, results are presented and discussed. Finally, the conclusion section reports the key findings, implications and limitations, and suggests future directions.

2. Literature Review

A critical review of relevant literature is provided as a theoretical foundation for this research. This section aims to understand the evolution of big data and BDA, its characteristics and techniques, to locate prior studies on BDA adoption and decision-making quality, and identify possible significant determinants of BDA adoption.

2.1. Big Data Analytics

Technological advancement has made human society increasingly responsive and connected as it generates vast volumes of data (big data) every second via the Internet of Things (IoT), sensors, management and financial systems, and user-generated data (Silva et al., 2019). However, the real value of big data is realized when meaningful insights and decisions are taken based on it (Gandomi & Haider, 2015), known as BDA. There are two main underlying concepts behind BDA; data storage and data analysis (Yin, 2015). As shown in Figure 1, data is first recorded, cleaned and grouped, then algorithms, modeling and analysis are applied and, finally, interpretations are made (Khatri et al., (2021).

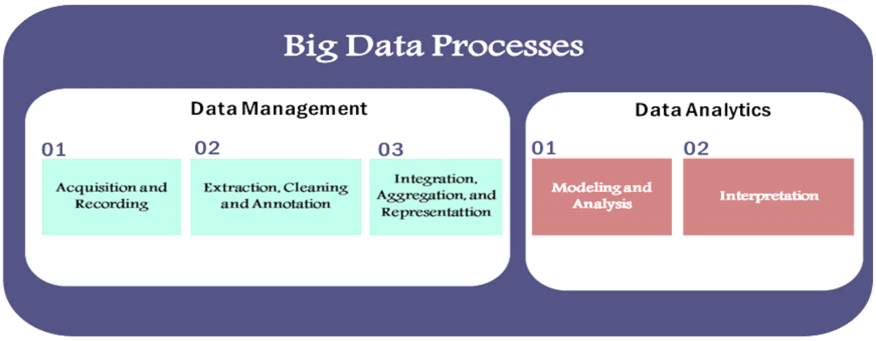

Fig. 1: Big Data Extraction Processes (Source: Khatri et al. (2021))

BDA is classified into four techniques: descriptive, diagnostic (past events), predictive, and prescriptive (future predictions) (Altarawneh et al., 2022; Ouyang et al., 2022) (Ghani et al., 2019; Ouyang et al., 2022; Sekar, 2022; Zarina Abdul Jabar et al., 2022), where future predictions are more complex and valuable than analyzing past events (2021).

2.2. Application of BDA in Public Sector

Digital transformation is perhaps the fundamental order-of-business for public organization to survive, staying competitive and adaptive to changes in the business landscape (Ang Subiyakto et al., 2023). There are many challenges associated with BDA beyond technical issues, and beyond a shift in culture towards data-driven decisions. Key challenges, in addition to separating valuable data from noise, include balancing analysis costs with data confidentiality, choosing a cloud computing service, and determining data retention periods (Alalawneh & Alkhatib, 2021). However, even with these challenges, many nations are leveraging the benefits of BDA in public sector organizations, including smart cities, healthcare, pharmaceuticals, and government. Among the potential benefits of BDA application:

- Employing BDA in Smart Cities, the government can take advantage of valuable real-time information on traffic statistics, construction, utility poles, water lines, transporters, weather conditions, criminal data, and tourist data to improve public services (Hashim et al., 2021; Wang et al., 2020).
- BDA in smart cities enables the unveiling of consumers' behavior to understand their needs in a better way and deliver public services better suited to those needs (including the creation of new services), as well as to verify eligibility for public services, allowances, and so on (Maciejewski, 2017).
- Vast amounts of healthcare data will enable authorities to anticipate which regions will be affected by various diseases (Silva et al., 2019).
- Healthcare practitioners may investigate human DNA to customize therapies and discover high-risk people; advance research into life-threatening disorders by aggregating data on common diseases; analyze and predict medication interactions and side effects; and identify individuals with certain biological traits who are eligible for specialized clinical studies (Kornelia & Andrzej, 2022).
- Detecting tax evasion and other anomalies is an excellent example of how BDA is used in the public sector (Maciejewski, 2017).
- Analysts will be able to spot abnormalities in financial markets (Maciejewski, 2017).

2.3. Development of Concepts for BDA adoption and Decision-making Quality

A systematic literature review (SLR) was performed to discover the determinants of BDA adoption mentioned in existing literature, so that a conceptual model can best support the discovery of determinants and assessment for BDA adoption and decision-making quality among public sector organizations in Oman. According to Lame (2019), compared with the traditional literature review, SLR employs a more scientific approach to the review process by using concepts from empirical research to make the review more transparent, replicable, and free from bias. Following the guidelines of Templier and Paré (2015), a flow chart of SLR is illustrated in Figure 2. The first step pertains to a problem statement: the demands of BDA adoption have been discussed in the Introduction.

The second step involved selection of scholarly databases (Google Scholar, IEEE, Web of Science, ScienceDirect, and Emerald), using multiple search commands. In the third step, the search command was run on the selected database and found 143 studies, which was reduced to 60 by filtration. The papers were thoroughly screened for relevance in step four by looking at the abstract, introduction, discussion and conclusion of each, after which 48 relevant studies remained. Finally, steps five and six pertain to the development of the model and hypotheses. The analysis revealed that a majority of the final sample studies, amounting to 23, were based on the TOE (Technological Organizational Environment) model. Khurshid et al. (2020) claim that, in the domain of open government data, the Technology-Organization-Environment (TOE) framework is the most commonly utilized among theories and models of innovation adoption. Therefore, based on the SLR, the study identified the use of the underpinning TOE theory as the best option to adopt for the development of a conceptual model for BDA adoption and its impact on decision-making quality. The prominent factors for each TOE aspect are further analysed and discussed for relevance to the BDA adoption model and the formation of hypotheses and the conceptual model (see Figure 2).

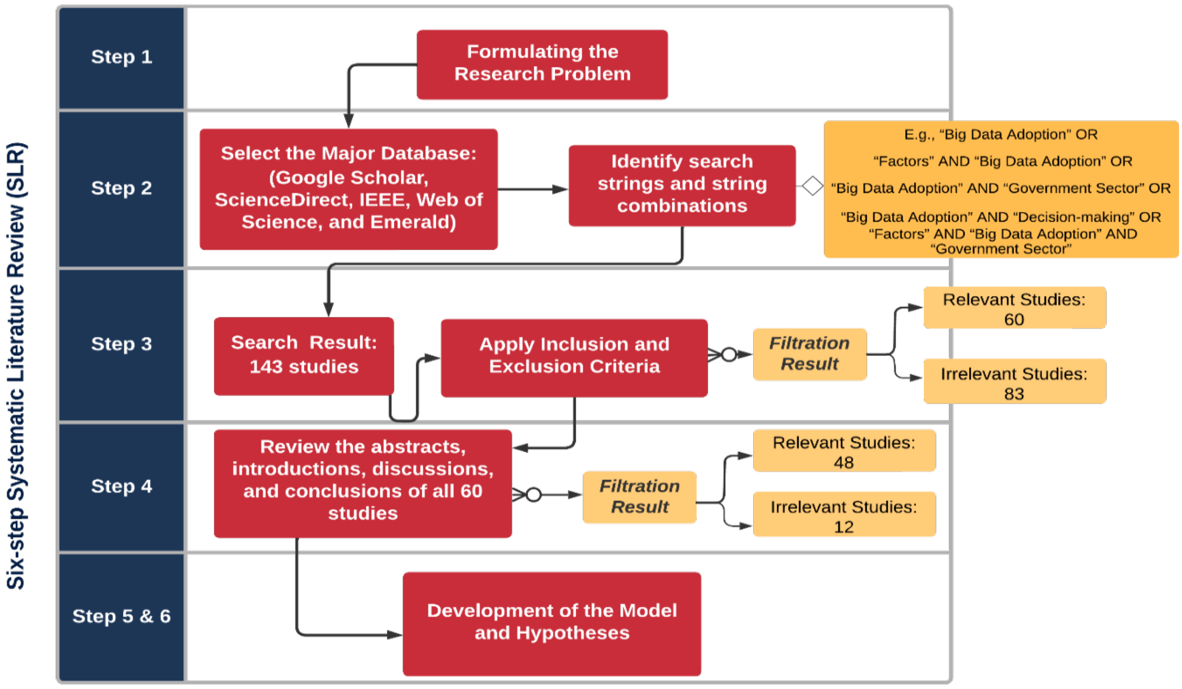

Fig. 2: SLR Workflow Chart

2.4. Technology Factors

Based on the SLR synthesis, the study underscores technology as an important aspect and includes relative advantage, complexity, compatibility, and insecurity for BDA adoption and decision-making quality in the public sector.

- Relative Advantage

Relative advantage refers to the extent to which an innovation is seen as better than the idea or concept it replaces (Alaskar et al., 2021; Baig et al., 2021; Rogers, 2010). Considering Rogers' (2003) theory of innovation, the adoption, acceptance, and spread of new technologies often accelerate when these technologies are perceived to possess specific attributes: relative advantage, complexity, compatibility, trialability, and observability. However, studies using this framework suggest that three technical attributes, namely relative advantage, compatibility, and complexity, consistently hold greater significance in the adoption process (Ekong et al., 2012). Furthermore, the rate of adoption of an innovation will be quicker when the relative advantage is higher (Rogers, 2010). Prior studies stated that it had been used to expand opportunities, enhance user services, and boost competition (Baig et al., 2021). Yadegaridehkordi et al. (2020) claim there is no motivation to adopt and exploit big data in businesses without first identifying its advantages and benefits. This prompted the development of the following hypothesis:

H1. *Relative advantage positively affects BDA adoption*

- Complexity

Complexity is defined as "The extent to which an innovation is seen as comparatively hard to understand and use" (Rogers, 2010). Gangwar et al. (2015), stated that complexity could be measured in terms of task completion time, data transmission effectiveness, system functionality, and interface layout. Since complexity is linked to a high level of uncertainty, it is seen as a barrier that might prevent organizations from adopting IT advancements (Alaskar et al., 2021; Baig et al., 2021; Gangwar et al., 2015; Lai et al., 2018). In this regard, Baig et al. (2019), made the case that the complexity of BDA may be a significant factor in deterring many organizations from moving forward with the adoption process. As a result, the following hypothesis is suggested:

H2. *Complexity negatively impacts the BDA adoption*

- Compatibility

Compatibility refers to the degree to which new technology is perceived to be compatible with the current principles, experiences, and requirements of potential adopters (Rogers, 1995). Furthermore, compatibility evaluates the extent to which a new system seamlessly integrates with the current systems of the organization (Maroufkhani et al., 2020). Since big data is unstructured, abundant, and moving quickly, developers must build new skill sets to leverage big data tools and technologies (Rahman et al., 2021). Yadegaridehkordi et al. (2020), claim that innovations that are compatible with the current technologies and standards are adopted more quickly than those that are not. Thus, this leads us to the following hypothesis:

H3. *Compatibility is positively affecting BDA adoption.*

- Insecurity

Insecurity refers to the risk associated with the adoption of any innovation, which inhibits innovation adoption in the institution (Alshamaila et al., 2013). According to (Lutfi et al., 2022; Maroufkhani et al., 2020). When embracing any innovation related to data, security and privacy emerge as the most common worries associated with the adoption process. Insecurity involves a sense of doubt regarding the safety and reliability of engaging in online transactions and sharing information. Lin (2023) suggests that the perception of insecurity not only acts as a hindrance to the adoption of IT innovation but also results in negative outcomes, such as the disclosure of private information and poor system performance. Big data technology must be able to safeguard sensitive information (Rahman et al., 2021). Prior studies have indicated that big data applications must meet some specific prerequisites, such as governing sensitive data relating to people, companies, and countries (Lee, 2017; Menon & Sarkar, 2016). As a result, the following hypothesis is proposed.

H4. *Insecurity negatively impacts the BDA adoption.*

2.5. Organizational Factors

The organizational dimension illustrates various organizational factors that influence readiness for BDA adoption (Giang & Liaw, 2022). Organizational data environment, business strategy orientation, company size, and industry type are all factors of the organizational dimension (Nasrollahi et al., 2021). Consequently, this study considered top management support, organizational readiness, and organizational size, as discussed below.

- Top Management Support

Top management support refers to the level of commitment and endorsement demonstrated by senior management towards technological innovation (Alaskar et al., 2021). Nevertheless, the support of decision-makers, typically part of the top management team, is pivotal for innovation adoption within organizations, acting as the primary bridge between individual and organizational technology adoption, with the level of top managers' innovativeness directly influencing the overall adoption level (Maroufkhani et al., 2020). Management support encourages a company culture that is positive towards IT adoption and the provision of the needed resources, financial funding, and human resources, which are considered necessary for any IT adoption (Yin, 2015). Therefore, this study proposes the following:

H5. *Top management support positively affects BDA adoption.*

- Organizational Readiness

Organizational readiness can be described as the ability and willingness to make available particular organizational resources required to implement innovations in IT (Alaskar et al., 2021; Chen et al., 2015; Gangwar, 2018). The required resources are typically divided into three groups (Alaskar et al., 2021). The organization's capacity to allocate financial resources to IT innovation comes first. The second technological resource is the IT infrastructure, encompassing databases, applications, and technical platforms essential for storing, processing, and analyzing extensive data. The third resource is human resources, which refers to the pool of IT experts who are able to work on big data projects. (Alaskar et al., 2021; Chen et al., 2015; Clohessy & Acton, 2019; Gangwar, 2018). Thus, this study postulates the following:

H6. *Organizational readiness is positively affecting BDA adoption.*

- Organization Size

Organizational size is considered one of the most extensively investigated innovation adoption factors (Gangwar, 2018). It is defined as the number of workers in a specific organization (Yadegaridehkordi et al., 2020). Mahesh et al. (2018), argue that various previous studies have revealed that organization size is an essential factor influencing IT adoption. Yadegaridehkordi et al. (2020), stated that larger organizations are undoubtedly the first to adopt any innovation because they have access to more resources and can take on more significant risks. Smaller businesses, on the other hand, experience resource poverty and have great difficulty managing the considerable investment needed for adequate adoption. Nevertheless, the literature indicates that the relationship between organizational size and technology adoption initiative is inconclusive; as a result, some empirical studies have revealed a positive relationship, while others reported a negative one (Gangwar, 2018). Thus, the following hypothesis is proposed:

H7. *Organization size positively affects BDA adoption.*

2.6. Environmental Factors

The environmental dimension includes external factors that the organization may confront in BDA adoption; this study investigates competitive pressure and government regulation as the environmental factors that may influence BDA adoption.

- Competitive Pressure

Competitive pressure is viewed as a crucial environmental element since it mirrors the state of technology utilization, hence pressuring companies to cause a change and accept new technical innovations (Alaskar et al., 2021). Porter and Millar (1985) theorized that competitors adopting IT innovations have the potential to reshape the competitive landscape by altering the rules of the game and introducing entirely new value propositions and enterprises. Consequently, numerous businesses find themselves obligated to leverage cutting-edge technology to sustain their competitive edge and achieve a competitive advantage. Perceived competitive pressure is a powerful motivator for the use of big data analytics, according to Yin's (2015) research. Hence, organizations can gain more business value and remain competitive by using big data strategically (Rahman et al., 2021). In this regard, this study proposes:

H8. *Competitive pressure has a positive effect on BDA adoption.*

- Government Regulations

Government regulation is the assistance and direction given by the government to a company for creating and adopting new technologies (El-Haddadeh et al., 2021). In general, government policies and regulations are mostly prohibitions, but these rules and regulations can occasionally motivate businesses to adopt a particular type of new technology (Maroufkhani et al., 2020), while companies facing extensive regulations and government pressure are generally more likely to adopt technological innovation. Furthermore, government rules have the power to encourage or discourage businesses considering whether to embrace cloud technologies (Ghaleb et al., 2021). Ghaleb et al. (2021) further suggested that prior empirical studies had identified government regulations and legislation as major factors affecting the adoption of cutting-edge technologies like enterprise resource planning (ERP) and cloud computing, especially in developing countries. Thus, this study suggests:

H9. *Government regulation positively affects BDA adoption.*

2.7. BDA Adoption

The literature suggests that the public sector can benefit significantly from BDA by gaining a better understanding of current challenges, external environments, and citizens' needs to assist in improving policies and services. A variety of complex social issues can be addressed using BDA, which can support the public sector in making better decisions, boosting economic growth, and managing many difficult problems (Vasilyeva & Richardson, 2022). In a recent report, 49% of organizations claimed that BDA improves their decision-making ability; consequently, numerous organizations have begun to process BDA to improve their decision-making techniques (Ghasemaghaei & Calic, 2019). According to Janssen et al. (2017), little attention has been paid to exploring how BDA may influence organizations' decision quality. Organizations can gain confidence in their ability to improve organizational decisions by processing big data and shifting from experiential to analytical decision-making. On this basis, the following hypothesis is proposed.

H10. *BDA adoption positively impacts decision-making quality*

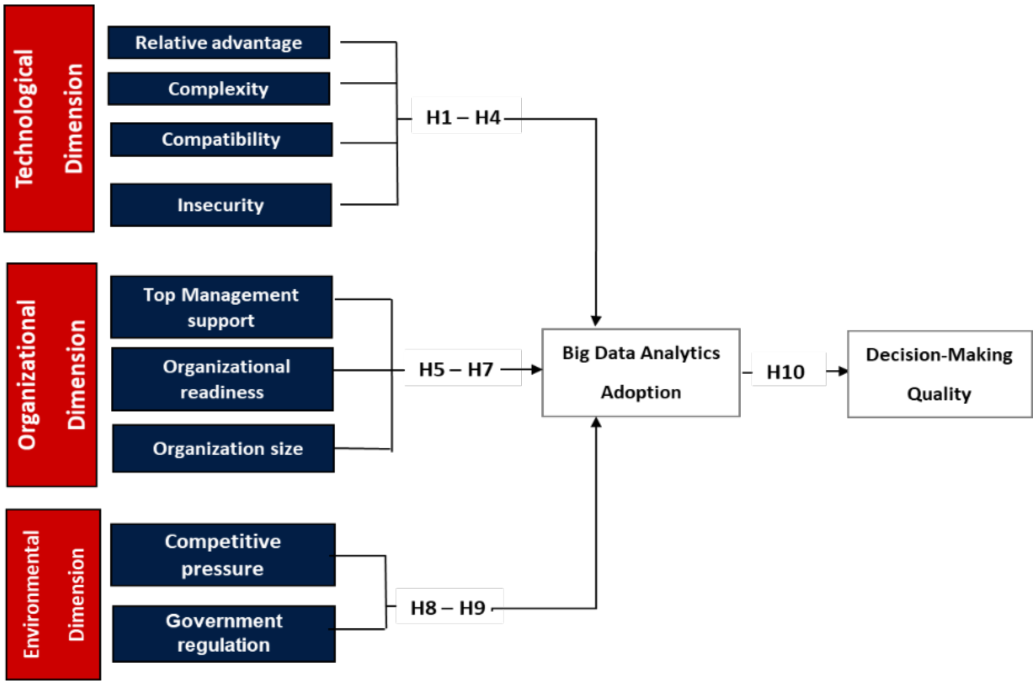

Fig. 3: Proposed research model

3. Methods

This section explains the research strategy underlying this study, including data collection analysis. It reports how the study was conducted, including the processes, techniques, and steps involved. The research employed quantitative methods because this allows researchers to measure the instrument's condition, enabling them to decide an instrument's maturity (Ivarsson et al., 2009). This study attempts to contribute to a greater understanding of the BDA adoption phenomenon in the context of the public sector in Oman. As a result, the study began with a systematic review of literature to identify the most frequent and supported factors that directly affect BDA adoption to develop the study framework and hypotheses. Subsequently, data were collected from public sector organizations in Oman, and a quantitative analysis was conducted using partial least squares structural equation modeling (PLS-SEM) techniques. The selection of these organizations was based on their accessibility to the researcher. Given the study's objectives and nature, a non-probability convenience sampling technique was employed to reach an accessible population for data collection. This technique is suitable when a study necessitates a specific criterion, requiring a non-random population (El-Masri, 2017). The determination of the sample size generally considers three factors: the type of distribution (observed variables), model complexity, and the estimation method (Dash & Paul, 2021). This study utilized Smart-PLS 4.0 to assess reliability and validity through the PLS algorithm, verifying or rejecting structural model hypotheses via Bootstrapping. The sample size was determined by the widespread use of Smart-PLS in technology adoption studies, its acceptance of small sample sizes (at least 100 participants), and its capacity to explore relationships between observed and latent variables, encompassing exogenous and endogenous latent variables (Acikgoz et al., 2023).

3.1. Research Instrument

The study employs a cross-sectional design, since BDA is a new field, and it is not possible to collect adequate responses at multiple points (Rahman et al., 2021). The questionnaire items in this study were adapted from constructs previously validated by other scholars in the profession (See Appendix A.1). Straub (1989), suggests that reusing previously validated instruments is good practice when using questionnaire methodologies. Furthermore, using pre-existing measures has the benefit that they have already been tested for reliability and validity, allowing the researcher to have confidence in the accuracy of the measurements without having to evaluate them (Alnakhli, 2019). The study used a 7-point Likert scale to obtain responses for each measurement item.

3.2. Data Collection

This study aimed to reach employees working in the information technology function of public sector organizations in Oman. Data collection was conducted using a cross-sectional survey questionnaire. Most studies now choose to use online questionnaires since they can be accessed and shared with less expense and time. They are especially popular after the global COVID-19 pandemic issue because they need not involve person-to-person contact (Coşkun & Dirlik, 2022). Also, the use of an online questionnaire is an optimal strategy for gathering and evaluating the data by statistical packages such as SPSS and SmartPLS 4 for descriptive statistics and SEM-PLS analysis as in this study.

Prior to data collection the researcher received ethical approval to distribute the questionnaire as an official procedure of Sultan Qaboos University. A total of 332 responses were gathered from IT professionals within the public sector in Oman.

3.3. Data Analysis

Before going for formal data analysis, researchers suggest that data screening should be performed to identify and handle issues of missing values, normality, and collinearity. A normality assumption means the sample was drawn from a normally distributed population (Tsagris & Pandis, 2021). In light of this, when considering statistical analysis, it is essential to pay attention to assumptions such as normality, as failure to adhere to these assumptions can lead to inaccurate and unreliable conclusions about the collected data and reality (Ghasemi & Zahediasl, 2012). Structural Equation Modeling (SEM) is employed to analyze complex statistical relationships by visualizing and evaluating the model to comprehend the connection between latent constructs, which are typically represented by multiple measures (Dash & Paul, 2021). Because the relationship is based on variance, rather than covariance (AlNuaimi et al., 2021), the partial least squares (PLS) approach has recently gained much attention among researchers. According to Dash and Paul (2021), SEM is a versatile tool that can be used to analyze both experimental and non-experimental data and cross-sectional and longitudinal data; its flexibility and broad applicability have made it a popular method across many disciplines. The first stage in formal analysis for PLS-SEM is estimation of the measurement model. Prior studies have established that the validity of a reflective measurement model can be determined by assessing its internal consistency, indicator reliability, and construct validity (convergent validity and discriminant validity) (Alnakhli, 2019). The second stage is estimation of the structural model, which follows the guidelines of Hair Jr and Sarstedt (2019) to evaluate the structural model. It guides estimations to determine for collinearity, model fit, effect size, path coefficients, coefficient of determination (R2), and predictive relevance.

4. Results

The purpose of this study is to understand the impact of critical factors on Big Data Analytics (BDA) and the association between BDA and the quality of decision-making. Therefore, this study uses quantitative methods to understand, examine, and measure these relations. To achieve this measurement, the proposed model for this study adds nine latent variables and one mediating variable, as shown in Figure 3.

4.1. Data Screening

The first step of data screening looks for any missing data or values in the collected responses. Out of 332 total responses, 0 were found to be incomplete. Outliers were detected using the STDEV.P formula in an Excel file on each row, and the data were uploaded to SPSS for analysis with the regression method, which identified 11 outliers with values below 0.5. These were removed. For a more robust analysis of the normality distribution, a Skewness and Kurtosis test was performed: the resulting values, as shown in Table 1, were within permissible limits, i.e., skewness between -3 and +3 and kurtosis between -10 and +10. Finally, a multi-collinearity test was performed, yielding values in the acceptable VIF range of 0.2 to 5.00 (Albawwat et al. (2021). The screening process yielded a sample size of 321, and 44 reflective items were used to measure the constructs of the proposed model.

Table 1: Skewness and Kurtosis Results

Construct	Skewness		Kurtosis	
	Statistic	**Std. Error**	**Statistic**	**Std. Error**
Relative Advantage	-.531	.136	-.068	.271
Compatibility	-.387	.136	-.261	.271
Complexity	-.063	.136	-.520	.271
Insecurity	-.670	.136	.133	.271
Organizational Readiness	.128	.136	-.822	.271
Top Management Support	-.896	.136	.791	.271
Organization Size	-1.197	.136	1.455	.271
Competitive Pressure	-.339	.136	-.842	.271
Government Regulation	-.881	.136	.244	.271
BDA Adoption	-.449	.136	-.347	.271
Decision-making Quality	-.584	.136	.335	.271

4.2. Descriptive Analysis

The descriptive statistics provide insight into the demographic profiles of the respondents, as presented in Table 2. The total sample consisted of 321 participants who work in the public sector of Oman, with a focus on those employed in IT departments. Notably, the majority of the sample comprised males, constituting 63% of the total participants. Further analysis indicates that 40% of respondents fell within the age range of 35 to 44, while 33% possessed work experience in the field spanning 6-10 years. Regarding organizational affiliations, 25% of participants were affiliated with ministries, 36% with government organizations, and the remaining 39% belonged to other public sector entities, such as the Oman Council and Shura Council.

Table 2: Respondents' Profile

Categories	Sub-Categories	Frequency	Percentage
Gender	Male	201	63
	Female	120	37
Age	18-24	45	14
	25-34	91	28
	35-44	127	40
	45-54	44	14
	>55	14	4

Working Experience	1-5	64	20
	6-10	105	33
	11-15	79	24
	>16	73	23
Organization Type	Ministry	82	25
	Government	115	36
	Other	124	39

4.3. Measurement Model

The data analysis for the measurement model was performed using PLS-SEM with SmartPLS 4.0 software. The important tests for the measurement model are to find internal consistency, reliability and construct validity (Alnakhli, 2019).

Internal Consistency

Internal consistency is measured using Cronbach's alpha and composite reliability (CR) (Alnakhli, 2019): a higher value indicates the items within the construct are consistent in terms of range and meaning (Cronbach, 1971). In research, an internal consistency value of at least 0.7 is considered acceptable for early stages, and values above 0.8 or 0.9 are desired for more advanced stages (Alnakhli, 2019). The results, shown in Table 3, showed that the values of Cronbach's alpha were in the acceptable range, at 0.771 to 0.867, and CR values for each construct fell between 0.850 and 0.906, indicating satisfactory internal consistency and reliability of the items used to measure the constructs.

Indicator Reliability

Indicator (factor) reliability is determined by squaring the standardized loading of an indicator; this reflects the amount of variation in the item that can be attributed to the construct and is commonly referred to as the variance extracted from the item (Hair Jr et al., 2021). Table 3 shoes that the factor loading for each construct was found to be acceptable, with values of > 0.7 (Chin, 1998).

Convergent Validity

Convergent validity was assessed through the examination of Composite Reliability (CR) and Average Variance Extracted (AVE) (Acikgoz et al., 2023). The threshold limits of AVE should be greater than 0.5 (Alnakhli, 2019). Table 3 indicates that the AVE for all constructs ranges from 0.584 to 0.748, indicating that the measurement model has acceptable convergent validity.

The results of the three analyses detailed earlier are presented in Table 3. The relevant thresholds are as follows: Factor loadings > 0.7; Cronbach's alpha >= 0.7; composite reliability >= 0.7, AVE > 0.5

Table 3: Reliability, Factor Loading, and Convergent Validity

Constructs	Item	Factor Loadings	Reliability		AVE
			Cronbach's Alpha	Composite Reliability	
Relative Advantage	RA1	0.777	0.771	0.850	0.588
	RA2	0.820			
	RA3	0.763			
	RA4	0.703			
Compatibility	CM1	0.857	0.828	0.880	0.647
	CM2	0.842			

	CM3	0.776			
	CM4	0.738			
Complexity	CO1	0.700	0.859	0.901	0.696
	CO2	0.877			
	CO3	0.881			
	CO4	0.865			
Insecurity	IS1	0.849	0.845	0.896	0.684
	IS2	0.856			
	IS3	0.870			
	IS4	0.724			
Organizational Readiness	ORG1	0.888	0.862	0.884	0.657
	ORG2	0.845			
	ORG3	0.778			
	ORG4	0.721			
Top Management Support	TMP1	0.804	0.846	0.897	0.686
	TMP2	0.854			
	TMP3	0.851			
	TMP4	0.802			
Organization Size	OS1	0.949	0.855	0.880	0.649
	OS2	0.769			
	OS3	0.764			
	OS4	0.722			
Competitive Pressure	CP1	0.847	0.780	0.871	0.693
	CP2	0.845			
	CP3	0.805			
Government Regulation	GR1	0.832	0.865	0.906	0.708
	GR2	0.879			
	GR3	0.885			
	GR4	0.765			
BDA Adoption	BDA1	0.878	0.831	0.899	0.748
	BDA2	0.853			
	BDA3	0.864			
Decision-making Quality	DMQ1	0.740	0.867	0.893	0.584
	DMQ2	0.711			
	DMQ3	0.721			
	DMQ4	0.854			
	DMQ5	0.825			
	DMQ6	0.721			

Discriminant Validity

Discriminant validity assesses whether the items are unconsciously assessing anything besides the intended construct (Alnakhli, 2019). It is measured by tests of the Fornell and Larcker criterion and heterotrait–monotrait ratio (HTMT) (Acikgoz et al., 2023). Fornell and Larker's criterion compares the square root of AVE with the correlation among latent scores (Putra, 2022); the square root of AVE should be higher than the corresponding latent variable score. Table 4 shows that the square root of each construct's AVE has a greater value than the correlations with other latent constructs, confirming that Fornell and Larker's criterion is met. Bold diagonal elements in Table 4 represent the AVE for the relevant construct.

Table 4: Discriminant Validity by Fornell–Larcker Criterion

Construct	BDA	CM	CP	CO	DMQ	GR	IS	OS	ORG	RA	TMS
BDA Adoption (BDA)	**0.865**										
Compatibility (CM)	0.284	**0.804**									

Competitive Pressure (CP)	0.429	0.159	**0.832**								
Complexity (CO)	-0.248	-0.039	-0.121	**0.834**							
Decision-making Quality (DMQ)	0.143	0.197	-0.031	0.013	**0.764**						
Government Regulation (GR)	0.401	0.239	0.348	-0.094	0.299	**0.842**					
Insecurity (IS)	0.258	0.233	0.184	0.062	0.177	0.225	**0.827**				
Organization Size (OS)	0.074	0.104	-0.016	0.111	0.179	0.154	0.101	**0.806**			
Organizational Readiness (ORG)	0.164	0.051	0.193	0.122	-0.085	-0.003	0.064	-0.109	**0.810**		
Relative Advantage (RA)	0.361	0.335	0.140	-0.293	0.215	0.280	0.036	0.070	0.050	**0.767**	
Top Management Support (TMS)	0.325	0.320	0.101	-0.138	0.267	0.285	0.348	0.338	-0.075	0.303	**0.828**

The other measure is HTMT, which measures correlation among constructs. An HTMT threshold score below 0.90 is recommended for conceptually similar constructs, and below 0.85 for distinct constructs (Hair Jr et al., 2021). Table 5 demonstrates that all values fell below the threshold, indicating the achievement of discriminant validity.

Table 5: Discriminant Validity by Heterotrait–Monotrait Ratio (HTMT)

Construct	BDA	CM	CP	CO	DMQ	GR	IS	OS	ORG	RA	TMS
BDA Adoption (BDA)											
Compatibility (CM)	0.312										
Competitive Pressure (CP)	0.524	0.192									
Complexity (CO)	0.272	0.107	0.135								
Decision-making Quality (DMQ)	0.144	0.196	0.073	0.084							
Government Regulation (GR)	0.454	0.255	0.431	0.125	0.308						
Insecurity (IS)	0.297	0.297	0.227	0.078	0.195	0.257					
Organization Size (OS)	0.073	0.121	0.054	0.161	0.245	0.206	0.151				
Organizational Readiness (ORG)	0.139	0.101	0.233	0.206	0.162	0.057	0.099	0.165			
Relative Advantage (RA)	0.427	0.357	0.182	0.318	0.293	0.315	0.089	0.092	0.090		
Top Management Support (TMS)	0.385	0.372	0.119	0.161	0.296	0.327	0.404	0.388	0.139	0.363	

4.4. Structural Model Measurement

Once the prerequisite tests for the structural model were met, then the study proceeded with the measurement of structural model assessments such as GoF, R^2, F scores, path coefficients and Q^2.

Goodness of Model Fit

The goodness of fit (GoF) test was developed to measure model fitness in PLS-SEM by looking at scores of the Standardized Root Mean Square Residual (SRMR) criterion and the Normed Fit Index (NFI) (Neves, 2023). According to (Akbari et al., 2023 and Neves, 2023), it is considered acceptable if the SRMR is lower than 0.10 or 0.08 and the NFI value falls between 0 and 1, with a higher score indicating a better fit. Table 6 shows that the fit statistics for this study model were within acceptable ranges, with x^2 at 2285.587 and 856 degrees of freedom (df).

Table 6: Model Fit Indices

Measure	Model Output	Cut-off for good fit
Chi-square Test: x^2/df	2.67007	5 > Acceptable > 3 3 > Excellent > 1
NFI	0.698	0 > Acceptable > 0.9 NFI > 0.9 Excellent
SRMR	0.078	SRMR < 0.08

Coefficient of Determination (R^2)

The Coefficient of Determination (R^2) tells whether the variance in the response variable is caused by predictors estimated in the study (Hair Jr et al., 2021). Authors claim different threshold values but rule-of-thumb R^2 values of 0.75, 0.50, and 0.25 are generally considered substantial, moderate, and weak, respectively (Hair Jr et al., 2021). The R^2 values in this study were 0.499 for BDA adoption and 0.247 for decision-making quality.

Effect Size

The measure of effect size (f^2) determines the effect of predictors on the response construct (Salman & Normalini, 2021). Threshold values of 0.02, 0.15, and 0.35 are considered to predict small, medium, and large effect sizes, respectively, while values below 0.02 indicate no effect (Cohen, 1988). Table 7 displays the size of the effect found for the dependent variables in this study.

Table 7: Effect size (f^2) Measurement

Hypothesis	Effect size ($f2$)	Result
H1: Relative Advantage → BDA Adoption	0.030	Small
H2: Complexity → BDA Adoption	0.034	Small
H3: Compatibility → BDA Adoption	0.006	No effect
H4: Insecurity → BDA Adoption	0.015	No effect
H5: Top Management Support → BDA Adoption	0.018	No effect
H6: Organizational Readiness → BDA Adoption	0.023	Small
H7: Organization Size → BDA Adoption	0.000	No effect
H8: Competitive Pressure → BDA Adoption	0.089	Small
H9: Government Regulation → BDA Adoption	0.038	Small
H10: BDA Adoption → Decision-making Quality	0.021	Small

Predictive Relevance (Q^2)

Measuring the predictive power of the proposed model is an important test to consider. This study adopted an estimate of Stone-Geisser's Q^2 value (Geisser, 1974), to determine the predictive relevance of the model (F. Hair Jr et al., 2014). In this study, the values of Q^2 for BDA adoption and decision-making quality were 0.336 and 0.026, respectively, indicating a significant level of predictive relevance.

Path Coefficients

The estimation of path coefficients determines the significance and direction of a hypothesis. Table 8 illustrates the path coefficients, t-statistics, and significance levels for every proposed relationship. Based on the results from the path analysis, each proposed hypothesis can either be accepted or rejected.

Table 8: Path Analysis

Hypothesis	**Path Coefficient**	**Standard Deviation**	**t-Value**	**p-Value**	**Decision**
H1: Relative Advantage → BDA	0.157	0.049	3.190	0.001**	Supported
H2: Complexity → BDA	-0.157	0.050	3.132	0.001**	Supported
H3: Compatibility → BDA	0.069	0.050	1.396	$0.081^{n.s}$	Not Supported
H4: Insecurity → BDA	0.105	0.052	2.034	0.021	Supported
H5: Top Management Support → BDA	0.127	0.060	2.122	0.017	Supported
H6: Organizational Readiness → BDA	0.126	0.062	2.036	0.021	Supported
H7: Organization Size → BDA	0.010	0.071	0.140	0.444	Not Supported
H8: Competitive Pressure → BDA	0.260	0.055	4.738	0	Supported
H9: Government Regulation → BDA	0.174	0.055	3.136	0.001	Supported
H10: BDA → Decision-making	0.143	0.070	2.048	0.020	Supported

Table 8 illustrates that relative advantage is positively associated with BDA adoption (ß = 0.157, t = 3.190, p < 0.001), which supports H1. However, complexity negatively relates to BDA adoption (ß = -0.157, t = 3.132, p < 0.001), which supports H2. Insecurity is a statistically significant negative predictor of BDA adoption (ß = 0.105, t = 2.034, p > 0.021), so H4 is supported. Organizational readiness is also positively associated with BDA adoption (ß = 0.126, t = 2.036, p < 0.021), supporting H5. Moreover, top management support positively impacts BDA adoption (ß = 0.127, t = 2.122, p < 0.017), which supports H6. Competitive pressure positively affects BDA adoption (ß = 0.260, t = 4.738, p = 0), supporting H8. The results indicate that government regulation also positively relates to BDA adoption (ß = 0.174, t = 3.136, p < 0.001), supporting H9. Furthermore, BDA adoption positively relates to the quality of decision-making (ß = 0.143, t = 2.048, p < 0.020), which supports H10.

However, the statistical analysis indicates that compatibility does not explain BDA adoption (ß = 0.069, t = 1.396, p > 0.081); therefore, H3 is not supported. Moreover, organization size is not a statistically significant predictor of BDA adoption (ß = 0.010, t = 0.140, p > 0.444); thus, H7 is not supported.

The validated proposed structural model and the results related to the path coefficients (β), which represent the strength and direction of the relationships between the independent variables, mediator variable, and dependent variable in this study are displayed in Figure 4.

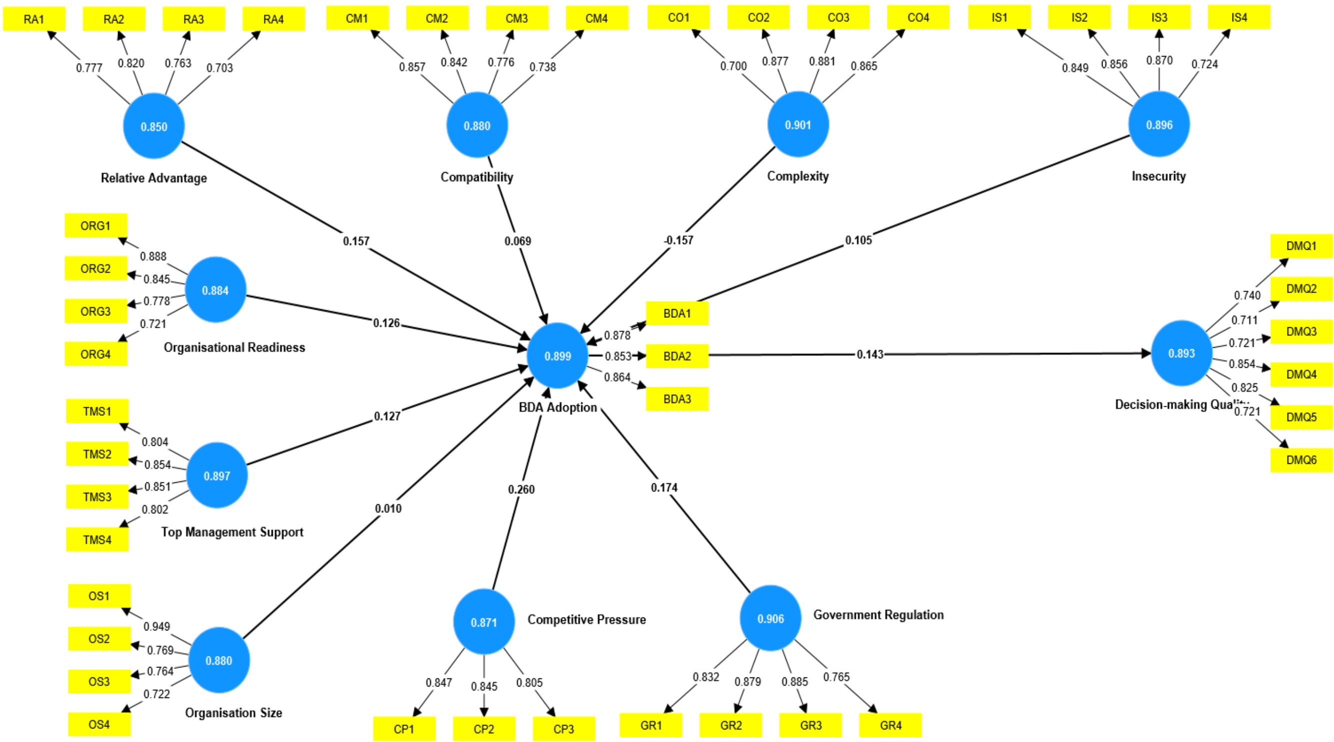

Fig. 4: Validated proposed structural model

5. Discussion

In this section, the results of the proposed research model are discussed, along with the findings from hypothesis testing. The aim is to provide a clearer understanding of the factors that impact the adoption of BDA and whether it can improve decision-making.

First, the results of technological aspects showed that, as hypothesized in H1, relative advantage has a positive influence on BDA adoption. In this regard, the strong impact of relative advantage on the adoption of BDA is in line with previous studies that also found a considerable influence (Baig et al., 2021; Lutfi et al., 2022; Sun et al., 2020). Organizations should acknowledge the advantages of Big Data Analytics (BDA) before adopting and using it; BDA offers numerous advantages, and there is no logical reason to encourage its adoption without acknowledging these benefits (Iranmanesh et al., 2022). Complexity (H2) is found to have a negative impact on BDA adoption, which means that recognizing the use of BDA during the adoption stage can be difficult due to its complexity. As stated by Gangwar et al. (2015), complexity can be evaluated through task completion time, data transmission effectiveness, and interface functionality. This result also aligns with previous research (Baig et al., 2021; El-Haddadeh et al., 2021; Lutfi et al., 2022). To overcome the perceived or actual complexity of BDA technology, technical training programs and compatibility/integration processes must be developed to facilitate successful adoption.

The non-significant results for H3, compatibility's effect on BDA adoption, contradicts previous studies (Baig et al., 2021; Ghaleb et al., 2021; Maroufkhani et al., 2020). A plausible explanation for this in Oman could be the complicated nature of procedures and practices of public sector organizations when it comes to acquiring the costly and advanced infrastructure needed to adopt such technology, which requires approvals from other government regulatory entities. Another reason could be that the recruitment process for talent within Oman's government is currently regulated solely by the Ministry of Manpower, which oversees the entire evaluation process. Alaskar et al. (2021) suggest that if organizational decision-makers perceive alignment between adopting a Big Data Analytics (BDA) system and existing organizational culture and practices, there is a greater inclination to adopt and implement it across various areas. This high perceived compatibility fosters a positive view of BDA, facilitating its adoption. However, our findings align with studies by Youssef et al. (2022), Lutfi et al. (2022), and Maroufkhani et al. (2020), which found no association between compatibility and BDA adoption. The result of H4 posits that insecurity has a negative impact on BDA adoption. This result is consistent with other studies showing that mistrust significantly hinders the uptake of many technologies (Baig et al., 2021; Lutfi et al., 2022; Maroufkhani et al., 2020; Youssef et al., 2022). As security and privacy measures have become increasingly robust, addressing concerns related to these factors has become more difficult during the BDA decision-making stage (Baig et al., 2021).

For organizational aspects, top management support (H5) was confirmed as having a significant effect on BDA adoption, which aligns with previous research (Baig et al., 2021; Lutfi et al., 2022; Youssef et al., 2022). Clearly, adopting new technology is a crucial decision that requires the support of top management and cannot otherwise be undertaken (Baig et al., 2021). Managers must inspire organizational changes by conveying their values and clarifying their vision to subordinates (Kandil et al., 2018). Furthermore, providing financial resources, human resources, and a corporate culture conducive to IT adoption should be the primary goals of top management (Yin, 2015).

The results indicate that H6, organizational readiness, plays a crucial role in determining the adoption of BDA and is a significant facilitator of the BDA process. The potent correlation found between organizational readiness and the adoption of Big Data Analytics (BDA) aligns with findings from earlier studies (Lutfi et al., 2022; Maroufkhani et al., 2020; Sam & Chatwin, 2018). Adopting Big Data Analytics (BDA) in Oman's public institutions might pose challenges without sufficient financial, technological, and human resources. This implies that an organization's likelihood of adopting BDA increases if it possesses the necessary resources and capabilities.

Contrary to the initial assumption underlying H7, the relationship between the size of organizations and the adoption of BDA was shown to be insignificant. Some previous studies have also observed it to be a less significant predictor than others (Jum'a et al., 2022; Sun et al., 2020; Yin, 2015). One potential explanation for this finding is that BDA solutions are becoming increasingly accessible to organizations of all sizes. In the past, implementing a BDA solution may have been prohibitively expensive for smaller organizations, but with the rise of cloud-based solutions and the availability of open-source tools, even small and medium-sized organizations can now leverage BDA technologies. Another possible explanation is that the benefits of Big Data Analytics (BDA) may not necessarily correlate with organizational size. Larger organizations, while having more data, could face increased complexity and inertia in adopting new technologies. In contrast, smaller organizations may be more agile and adept at quickly adapting to new technologies.

Two hypotheses related to environmental aspects and both were found to be significant. Under H8, competitive pressure was found to be the most influential factor in the adoption of BDA: this is confirmed by prior studies by Iranmanesh et al. (2022), Sun et al. (2020), and Pizam et al. (2022). Organizations often adopt new technologies or innovations due to competitive pressure (Yin, 2015), driven by the need to maintain a competitive advantage and stay ahead of rival businesses already utilizing BDA.

Also, the significant result of H9 implies the importance of government support and regulatory bodies in promoting the adoption of BDA. The decision to adopt technology can be influenced either positively or negatively by government regulations (Baig et al., 2021), but in line with previous studies, this study found that government regulations had a significantly positive effect on the adoption of BDA (Baig et al., 2021; Ghaleb et al., 2021; Lutfi et al., 2022; Sun et al., 2020). For instance, government regulatory support and financial incentives can help organizations overcome any financial or technical skill-related barriers to BDA adoption.

Finally, H10 indicates a notable and positive impact of BDA on the quality of decision-making. There are two plausible explanations: first, organizations are currently shifting towards making decisions autonomously, and BDA capacity encompasses a broad range of factors, including human expertise, technological resources, and managerial proficiency (Awan et al., 2021). Second, BDA enhances resource utilization: scholars have also proposed that the capability of organizational learning can facilitate the rapid generation of data-driven insights, leading to more efficient decision-making (Awan et al., 2021). These insights contribute to the development of analytics capabilities and inspire managers to promptly address problems and provide innovative solutions in real time.

6. Conclusion

Despite the increasing importance of Big Data Analytics (BDA) in decision-making, there is limited attention to how BDA capability influences organizational decisions (Awan et al., 2021). This study addresses this gap, providing theoretical insights into the factors and outcomes of BDA in Oman's public sector. The effective use of BDA in decision-making and problem-solving remains underexplored, with businesses recognizing its potential benefits, but the public sector lags behind (Akter et al., 2019; Coulthart & Riccucci, 2022; Elgendy & Elragal, 2016; Polese et al., 2019). This study contributes valuable insights into the impact of technological, organizational, and environmental factors on BDA adoption in the Omani government sector. Furthermore, this study reveals that the adoption of Big Data Analytics (BDA) in the Omani government sector is influenced by organizational, environmental, and technological factors. The practical implications underscore the importance of managers' and policymakers' consideration of these factors. The study also highlights the positive impact of BDA adoption on decision-making quality in government organizations. Despite discussions on BDA's effects on large corporations, there is a research gap concerning its connection to decision-making quality in the public sector. Nevertheless, our study's findings on the association between BDA and decision-making imply that Government organizations in Oman can enhance decision effectiveness by leveraging BDA tools for a transition to data-driven decision-making, despite existing uncertainties and lack of knowledge.

Moreover, this study has developed a conceptual model based on literature and incorporated decision-making quality. The study examined the adoption of BDA to improve decision-making quality, not only from a technical perspective but also from organizational and environmental points of view. The proposed model is tested empirically, resulting in the identification of seven significant factors and three non-significant factors. BDA shows great potential for enhancing public services, such as providing customized e-government services and improving decision-making through forecasting. Several countries view BDA as a means to address current social and economic problems and as a future growth engine (Kim et al., 2019). It is a crucial topic in the information systems literature due to its cutting-edge technology. Hence, the discovery and assessment of determinants of BDA adoption is paramount for the public sector of Oman to increase decision-making quality.

The first limitation of the current study is that the data collected from IT professionals were not compared with those collected from the business side, so it is challenging to understand potential differences or similarities in their perceptions and behaviors relating to the impact of BDA on decision-making quality. Secondly, this study gathered data through a questionnaire primarily completed by IT professionals. It is important to note that individual perceptions may not fully represent the organization's viewpoint. Additionally, the study's focus on IT professionals in public sector organizations may limit the generalizability of its findings. Future researchers may conduct a multi-level comparison of the perspectives of IT and business managers, and further include users' perceptions. Thirdly, the study is limited to considering linkages between the level of adoption and decision-making quality; however, it is also important to assess post-adoption developments. Future researchers could utilize qualitative methods to gather input from top management, middle management, and end-users about their experience of the contribution of BDA towards decision-making. Finally, future research can enhance generalizability by investigating a diverse range of organizations across multiple sectors, considering various demographics and characteristics.

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APPENDIX

A.1 Measurement Items

Variable	Measurements	Source
Relative Advantage	• The use of Big Data Analytics offers new opportunities. • Our organization believes that Big Data Analytics could improve customer services. • The use of Big Data Analytics services improves the quality of operations. • Big Data Analytics provides my organization with valuable information for decision-making	(Yadegaridehkordi et al., 2020), (Sun et al., 2020)
Compatibility	• Using Big Data Analytics is consistent with our business practices. • Using Big Data Analytics fits our organizational culture. • Overall, it is/will be easy to incorporate Big Data Analytics into our business practices. • Big Data Analytics can be easily integrated into the existing IT infrastructure	(Alaskar et al., 2021), (Baig et al., 2021)
Complexity	• The use of Big Data Analytics would require a lot of mental effort. • The use of Big Data Analytics would be frustrating. • Big Data Analytics would be too complex for our organization to use. • The skills needed to use Big Data Analytics would be too complex for us.	(Alaskar et al., 2021)
Insecurity	• Our organization has the ability to secure data. • Our organization has complied with Internet security. • Our organization has given top priority to the privacy of user's data. • The use of data analytics creates concerns about technological risks.	(Chong & Lim, 2022)
Organizational Readiness	• Our organization lacks the capital/financial resources to adopt Big Data Analytics • Our organization lacks needed IT infrastructure to adopt Big Data Analytics. • Our organization lacks analytics capability to adopt Big Data Analytics. • Our organization lacks skilled resources to adopt Big Data Analytics.	(Alaskar et al., 2021)
Top Management Support	• Top management would provide resources necessary for the adoption of Big Data Analytics. • Top management would provide necessary support for the adoption of Big Data Analytics. • Top management would support the use of Big Data Analytics. • Our top management promotes the use of Big Data Analytics in the organization.	(Alaskar et al., 2021)
	• I believe large organizations have the propensity to invest in innovations and have an	

Organization Size	advantage over SMEs (Small and Medium-sized Enterprises). • I believe large organizations can allocate resources and can take greater risks associated with Big Data Analytics adoption. • Number of employees is a significant indicator of Big Data Analytics adoption decision. • Number of employees enhance overall efficiency to adopt Big Data Analytics.	(Yaseen et al., 2022), (Baig et al., 2021)
Competitive Pressure	• Our choice to adopt Big Data Analytics would be strongly influenced by what competitors in the industry are doing. • Our organization is under pressure from competitors to adopt Big Data Analytics. • Our organization would adopt big data analytics in response to what competitors are doing.	(Alaskar et al., 2021)
Government Regulations	• Government organizations who provide training encourage our organization to adopt Big Data Analytics. • Government organizations who provide effective technical support encourage our organization to adopt Big Data Analytics. • The governmental policies encourage our organization to adopt Big Data Analytics. • The government provides incentives if our organization adopts Big Data Analytics.	(Maroufkhani et al., 2020), (Chong & Lim, 2022)
Adoption BDA	• Our organization intends to adopt Big Data Analytics. • Our organization intends to start using Big Data Analytics regularly in the future (E.g., For the coming five years). • Our organization would highly recommend Big Data Analytics for other organizations to adopt.	(Alaskar et al., 2021)
Decision-Making Quality	• Our organization believes that having, understanding and using data and information plays a critical role • Individuals within our organization need data for effective decision making • The adoption of Big Data Analytics enables our organization to improve decisions quality. • The adoption of Big Data Analytics enables our organization to improve decisions accuracy. • The adoption of Big Data Analytics enables our organization to improve decisions accountability. • Big Data Analytics is believed to be able to help organizational employees to make better decisions • and improve creativity.	(Ashaari et al., 2021), (Chong & Lim, 2022), (Bag et al., 2021)