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Determinants of behavioral intention to use big data analytics (BDA) on the information and communication technologies (ICT) SMEs in Jordan

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A B S T R A C T

Big Data Analytics (BDA) provides an important resource for businesses seeking to enhance their performance and gain a competitive advantage, although not all organizations are adopting BDA techniques, and small and medium-sized enterprises (SMEs) in Jordan have been slow in this regard, despite being key players in any healthy economy, and the fact that BDA adoption can be facilitated by using the Technology Acceptance Model (TAM). The purpose of this study is to investigate the drivers of behavioral intention among managerial-level employees in Jordanian ICT SMEs to adopt BDA through a quantitative correlational research approach. The TAM questionnaire was used to gather data from 271 online survey participants in Jordan using Google Forms. The target group included management level staff working in small and medium-sized ICT firms (SMEs). Confirmatory factor analysis (CFA) was used to evaluate the research instrument's reliability and validity, and structural equation modeling (SEM) was utilized to test the study's hypotheses. The findings revealed that perceived usefulness, perceived ease of use, and perceived “privacy and security” significantly influenced managerial-level employees' behavioral intention to use BDA in their organizations. The research findings also supported the application of TAM, and the results of the investigation indicated that managerial-level employees would be willing to use BDA techniques providing they were perceived to be useful, user-effortless, and posed little concern about privacy and security. Overall, the current study's results demonstrate that the suggested model had good predictive power, 51% of the variance in behavioral intention, and was therefore capable of predicting managers' intentions to use BDA.

1. Introduction

Over the last two decades, the volume of data accessible to organizations has increased rapidly. According to Hariri et al. (2019), users create 2.5 quintillion bytes of data every day, Google handles 3.5 billion searches per day, and Facebook users upload 300 million photos and post 510,000 comments everyday. As shown by Ahsaan and Mourya (2019), Twitter users post 277,000 tweets every 60 seconds, share 3,471,222 WhatsApp images, and post 216,000 new Instagram photographs every 60 seconds.

However, the creation of augmented data is not limited to social media users. The amount of data is a challenge in several fields, including manufacturing (Al-Rwaidan et al., 2023; Muda et al., 2022; Harahap et al., 2022). According to Tao et al.

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(2018), production systems create 1000 exabytes of data annually, and production processes were projected to generate 44 zettabytes of data by 2020. However, as Ahsaan and Mourya (2019) observe, the primary issue among practitioners is that data is generated too quickly for any useful analysis.

Implementing big data analytics technologies is one method for addressing the fast development of data production(O'Donovan et al., 2015; Attiany et al., 2023; Rahamneh et al., 2023; Bumblauskas et al., 2017). These technologies are often used by IT professionals to manage large data streams, derive value from data patterns, and enhance operational efficiency. Large organizations typically perform big data analysis because smaller and medium-sized organizations face challenges in adopting and employing such techniques, including data security concerns, the absence of organizational models, data protection and privacy concerns, and financial barriers, among others (Coleman et al., 2016).

This research is significant for broad academic, practitioner, and organization populations interested in Big Data Analytics (BDA) technology. Particularly, the larger community of information and communication technologies (ICTs) in small and medium-sized enterprises (SMEs) might benefit from the present study. The interest of decision makers in BDA has increased rapidly (Dubey et al., 2016; Lu & Xu, 2019), and there is also a rising interest in the prospect that BDA might transform enormous amounts of raw data into useful, valued insights (Kache & Seuring, 2017; Müller & Jensen, 2017).

However, many small and medium-sized enterprises (SMEs) in manufacturing, services, education, and other industries are unwilling to employ BDA owing to implementation issues (O'Donovan et al., 2015; AL-Zyadat et al., 2022; Khalayleh & Al-Hawary , 2022;Verma, 2017). This is significant because, by not using this cost-effective technology, small and medium-sized enterprises (SMEs) jeopardize their own existence in today's highly competitive marketplace. Indeed, many firms depend on BDA to turn huge amounts of raw data into useful information that significantly lowers their operational expenses, improves the quality of business choices, and provides solutions to IT issues (Felix et al., 2018; Alolayyan et al., 2022; Shahbaz et al., 2019; Al-Shormana et al., 2021; Alshawabkeh et al., 2022; Verma, 2017). However, despite the advantages of BDA, SMEs are unable to reap the potential benefits as efficiently as big firms (Coleman et al., 2016; Marolt et al., 2020). Consequently, the current research offers SMEs information that may support them in their BDA implementation and acceptance procedures.

This research aims to fill the gap in the literature about BDA usage in ICT SMEs in Jordan. Using the Technology Acceptance Model (TAM) as its theoretical framework, this research explores the behavioral intention to use BDA among Jordanian ICT SME's. No sufficient investigation of the direct correlations between the TAM major factors and the usage of BDA by ICT SMEs has been conducted to date (Coleman et al., 2016; Marolt et al., 2020; Ajimoko, 2018; Verma et al., 2018).

2. Literature review and hypotheses development

2.1 Big data and big data analytics (BDA)

Given the complexity of big data and the continual development of big data application, it is expected that the body of knowledge in this area will continue to expand (Alsghaier et al., 2017; Al-Nawafah et al., 2022; Al-Azzam & Alazzm, 2019; Yang & Bayapu, 2020; Al-Hawary & Obiadat, 2021; Al-Alwan et al., 2022). However, academics are presently experiencing difficulties establishing key theories and a general understanding of big data.

Nizam and Hassan (2017) defined big data as having five Vs: volume, variety, velocity, value, and veracity. Volume reflects the size of the data, variety indicates the multiple data sources, velocity characterizes the rate of data flow, value indicates the importance of the data, and veracity relates to the trustworthiness of the data sources. According to Jain (2016), big data is considered as huge volumes of data that potential users are unable to collect, keep, process, and analyze using traditional database applications and software package solutions.

As shown by Adnan and Akbar (2019), big data refers to huge data collections that include structured, semi-structured, and unstructured data. Nonetheless, Bayraktaroglu et al. (2019) reported that structured data is discussed in the majority of the existing research literature. Sebalj et al. (2016) advised that fast data growth will undoubtedly continue alongside advances in science and increased data output from unstructured data sources. Furthermore, Halaweh and Massry (2015) stated that the use of new technologies, such as BDA, produces uncertainty as a result of unrecognized opportunities and challenges that may lead to obstacles and issues for enterprises in today's extremely competitive market.

2.2 Big Data Analytics (BDA) Adoption

A review of the existing research reveals that BDA adoption is important not just for larger manufacturing organizations (Coleman et al., 2016), but also for SMEs; nevertheless, as stated by Coleman et al. (2016), SMEs have been highly suspicious adopters of BDA. While 25% of major enterprises in the United States have implemented BDA, Coleman et al. (2016) report that just 2% of SMEs have followed suit. This hesitant attitude among SMEs is frustrating since 99% of organizations are classified as SMEs, and these firms contributed \$5.9 trillion to the US economy in 2014(Kobe and Schwinn, 2018). Furthermore, in Jordan, SMEs account for almost 90% of all firms, contribute about half of the national GDP, and employ 60% of the workforce. As a result, the application of technology that might boost SMEs' competitiveness is critical for the Jordanian economy as well as global competitiveness (Kobe & Schwinn, 2018; Al-Tamimi & Jaradat, 2019). Literature review reveals that BDA presents both economic possibilities and obstacles for companies (Alsghaier et al., 2017, Felix et al., 2018), but that SMEs have greater hurdles in handling and exploiting big data in their endeavors to achieve competitive advantage than their much bigger counterparts (Ajimoko, 2018). However, the reluctance of SMEs to embrace BDA may constitute a significant threat to their competitiveness, and in instances where BDA has been introduced, implementation has been tardy (Ogbuokiri et al., 2015). Consequently, it is necessary to investigate the variables promoting BDA adoption. Indeed, the knowledge gathered from such research may increase awareness of how to establish the optimal circumstances for technology adoption, enabling IT professionals employed by SMEs to develop the optimal BDA-use alternatives for those businesses (Ajimoko, 2018).

In addressing such settings, Sharma and Mishra (2014) observed that research has shown that the usage of a new technology may involve "soft skills" in addition to behavior intention, technical abilities, and technical knowledge. Additionally, societal influence, beliefs, and mitigating circumstances must be considered while promoting the usage of new technology. Brock and Khan (2017) concur with Sharma and Mishra (2014), adding that the technology acceptance model (TAM) has been an integral part of BDA adoption research. However, they also demonstrate that the TAM does not account for human capabilities and practical knowledge, despite describing an individual's motivations for using the system. According to Ajimoko (2018), the TAM disregards business requirements, such as the cost of technology, which have a significant effect on the capacity and desire of SMEs to embrace particular technologies. In addition, Ajimoko (2018) observed that the TAM did not take into account crucial acceptance requirements for major organizational technologies, such as the support of top management, the perception of privacy and security, and organizational culture.

Despite these limitations, the TAM is well accepted by researchers in its many modifications and replications (Davis, 1989; Razmak & Bélanger, 2018; Al-Azzam et al., 2019). The TAM, which was derived from two prior theories, the Theory of Reasoned Action (TRA) and the Theory of Planned Behavior (TPB), is said to be a more trustworthy prediction of actual behavior than either of those theories (Davis, 1989; Olushola & Abiola, 2017). Furthermore, Yudhistira and Sushandoyo (2018) claimed that a considerable number of studies have shown the TAM's effectiveness in predicting individuals' behavioral intentions.

Davis (1989) suggests that, in addition to PU and PEOU, external factors be added since they may increase the TAM's capacity to predict technology users' adoption behavior. As a result of these suggestions, BDA adoption researchers added additional variables to the original model in an effort to increase its prediction potential (Shahbaz et al., 2019). As a result, it was determined that employing the TAM in the current study would be advantageous in establishing technology adoption variables that would aid in gaining a better understanding of BDA implementation in Jordanian ICT SMEs.

2.2.1 Perceived usefulness (PU)

Perceived usefulness is described as an individual's belief that using a new system would enhance his or her performance (Davis, 1989; Brock and Khan, 2017), and it is the most often employed factor and the primary driver of technology adoption (Venkatesh and Davis, 2000; Claes et al., 2015). In this research, PU is also expected to be the main factor influencing ICT SMEs' behavioral intentions to use BDA in Jordan. Previous research has also shown a positive relationship with reuse intention, which has been effectively quantified in a number of fields, including the big data domain (Weerakkody et al., 2017; Shin and Bohlin, 2020). The user will not have a favorable view of benefit until he or she has experienced the practical usefulness of BDA in SMEs. According to the TAM model principles, the present research posits that PU correlates positively with BI, which leads to the following hypothesis:

H_1: *PU positively influences managerial-level employees' BI to use BDA in ICT SMEs in Jordan.*

2.2.2 Perceived ease of use (PEOU)

Davis (1989) described PEOU as the degree to which one perceives that using a certain information system would be simple. Later, he argued that the simplicity of use of information systems and technologies will aid in increasing customer acceptability (Soon et al., 2016). Using an easy-to-use system will help in the improvement of both organizational and individual performance (Venkatesh and Davis, 2000; Brock and Khan, 2017). In the case of BDA, firms may enjoy advantages such as cost savings, risk management, and improved decision-making. BDA adoption is said to be driven by user preferences for simplicity of use in circumstances requiring varied and vast volumes of data (Shin and Bohlin, 2020). Furthermore, BDA adoption researchers noted a direct relationship between PEOU and PU. According to such studies, the greater the perceived ease of use a new technology has, the more likely it is to be considered advantageous to the user's performance (Sivarajah et al., 2017; Shin and Bohlin, 2020). Theoretically, directly, and indirectly, PEOU impacts the behavioral intention of management to use BDA PU. The next hypotheses were offered to examine the claim:

H_2: *PEOU positively influences managerial-level employees' BI to use BDA in ICT SMEs in Jordan.*

H_3: *PEOU positively influences the PU of BDA use in ICT SMEs in Jordan.*

2.2.3 Perceived privacy and security (PPS)

Privacy and security refer to the extent to which a user feels a certain system is secure and effective for transmitting and storing sensitive and/or personal information (Arpaci et al., 2015; Kurdi et al., 2023; Mohammad, 2019; Aityassine et al., 2022; Cui et al., 2018). Privacy and security are key components of every information system (Sivarajah et al., 2017), since worries about privacy and security prohibit the user from considering the system's advantages and discourage him or her from using it (Eldahamsheh et al., 2021).

Several studies have shown the significance of privacy and security in encouraging users to embrace different information system technologies (e.g., e-health record systems, Zandieh et al., 2008; cloud computing, e-markets, B2C e-commerce, Hartono et al., 2014; and healthcare, Shahbaz et al., 2019). Furthermore, BDA consumers continue to have concerns about data privacy and security as a result of information fraud, sensitive data hacking, and other forms of digital piracy (Ferguson, 2016; Broeders et al., 2017). Previous research on BDA adoption has not clearly highlighted the importance of data privacy and security in ICT SMEs (Broeders et al., 2017), but it does suggest that these concerns are major elements that may influence BDA adoption by SMEs.

Positive user perceptions of the technology's security and privacy level may influence its usefulness and ease of use, leading to higher adoption rates. As a result, companies with strong data security and privacy capabilities will be able to build more confident behavioral intentions to employ BDA. As a result, the following PPS hypotheses are presented in this research to examine the impact of this component on BI, PU, and PEOU:

H_4: *PPS positively influences managerial-level employees' BI to use BDA in ICT SMEs in Jordan.*

H_5: *PPS positively influences the PU of BDA use in ICT SMEs in Jordan.*

H_6: *PPS positively influences the PEOU of BDA use in ICT SMEs in Jordan.*

3. The research model

Following an analysis of the relevant literature, the TAM was utilized to depict the probable causality relationships between the predictor variables (PU, PEOU, and PPS)and the dependent variable (managerial-level employees' BI to use BDA in their organizations). The suggested model (Fig. 1) depicts BDA behavioral intention by postulating three immediate determinants: PU, PEOU, and PPS. It also suggests three indirect impacts on behavioral intention: PEOU through PU, PPS via PU, and PPS via PEOU. Figure 1 depicts the assumed correlations among the research variables.

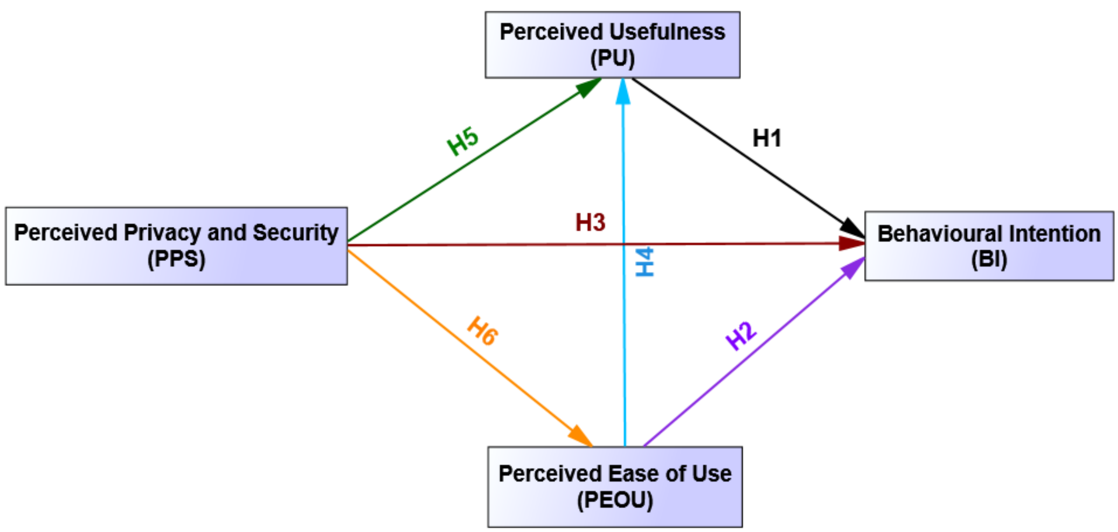

Fig. 1. The Research Model

4. Methodology

4.1 Research design

A quantitative correlation research methodology was utilized to examine if PU, PEOU, and PPS influence managerial-level employees' behavioral intention to use BDA in Jordanian ICT SMEs. The correlation research method enables the researcher to predict the value of one variable based on changes in another (Radhakrishnan, 2013). As a result, a correlation study approach was used.

During the data collection phase, participants completed a web-based survey that evaluated their understanding of the present study's parameters. Confirmatory factor analysis (CFA) using IBM AMOS software was used in the current study to examine correlations between observable and latent variables and to verify the measurement model's goodness-of-fit. Furthermore, structural equation modeling (SEM) (IBM AMOS) was used to evaluate the hypothesized correlations among the different constructs in the proposed model and to assess the goodness-of-fit of the structural model (Field, 2018; Hair et al., 2018; Byrne, 2013).

4.2 Target Population and Sample

According to ITAJ (2018), the study's target population was managerial-level employees in Jordanian ICT SMEs, who totaled about 2,000. A convenient sample of 271 participants was drawn from this population of SMEs in the ICTsector, including manufacturing, wholesale and retail trade, information and communication services, administrative and support service activities, and other service activities such as telecom value added services and modem repair. Employees at the management level of the selected SMEs were asked to participate by completing an online questionnaire containing relevant topics derived from a careful evaluation of the literature.

5. Results

From a distribution of 420 questionnaires using Google Forms invitations, 271 responses were obtained and considered valid for later quantitative analysis.

5.1 Demographic analysis

The pie charts in Fig. 2 summarize demographic characteristics such as gender, age, education, and management level; from this, it can be deduced that there were 72% males and just 28% females in the sample, closely resembling the gender distribution in the Jordanian ICTs sector. According to the ITAJ (2018), most management employees in ICT SMEs are men, with women representing only 28.4% of the sector's managerial workforce.

Figure 2 also shows that the number of respondents was greatest among those aged 51 to 60 (45%) and least among those older than 60 (8.3%). It also reveals that most participants (87%) are over the age of 41. This finding reflects the fact that the target group consists of individuals at the management level who typically do have many years of work experience.

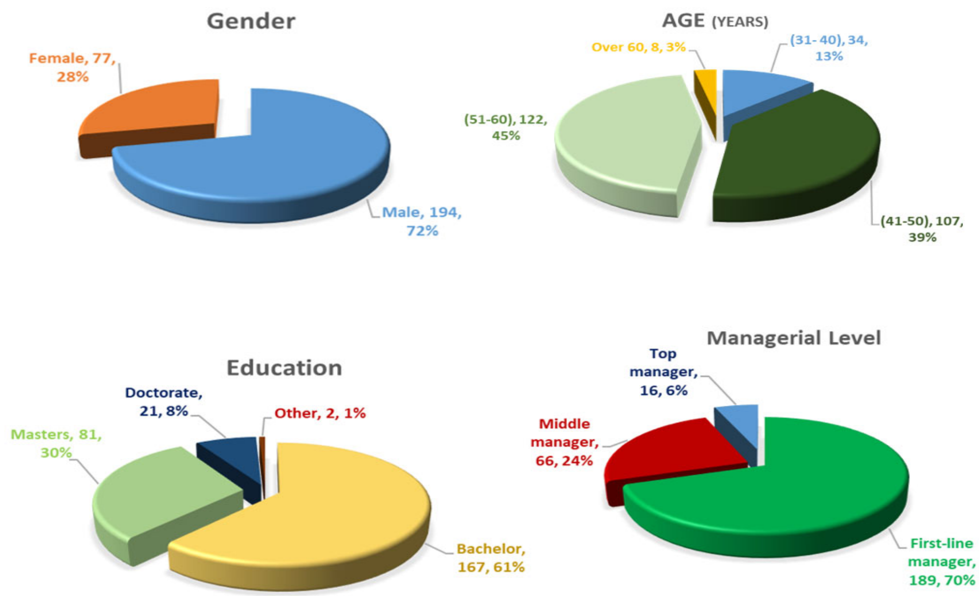

Fig. 2. Demographic Data of Study Respondents

Details of the educational backgrounds of the respondents show that most possess a bachelor's degree (61%), with graduate and post-graduate degree holders representing 30% and 8% of the whole sample, respectively. Two respondents, however, reported academic and technical college credentials as their educational backgrounds. This result reflects the high educational level attained by this managerial population. Responses came mainly from first-line managers, with only 16 top-level managers participating in the study.

5.2 Inferential Analysis

Confirmatory factor analysis (CFA) and structural equation modeling (SEM) for hypothesis testing make up inferential analysis (SEM). The following results were achieved after two stages of analysis:

5.2.1 Measurement Model: CFA

5.2.1.1 Measurement Model fit

Using IBM AMOS software, the measurement model depicted in Fig. 3 was constructed. Detailed goodness-of-fit results are shown in Table 1.It can be seen from reviewing Fig. 3 and Table 1 that all model indices exceeded levels of acceptance as suggested by earlier research thus demonstrating that the measurement model exhibited a good fit compared to the empirically collected data (Fornell & Larcker, 1981).

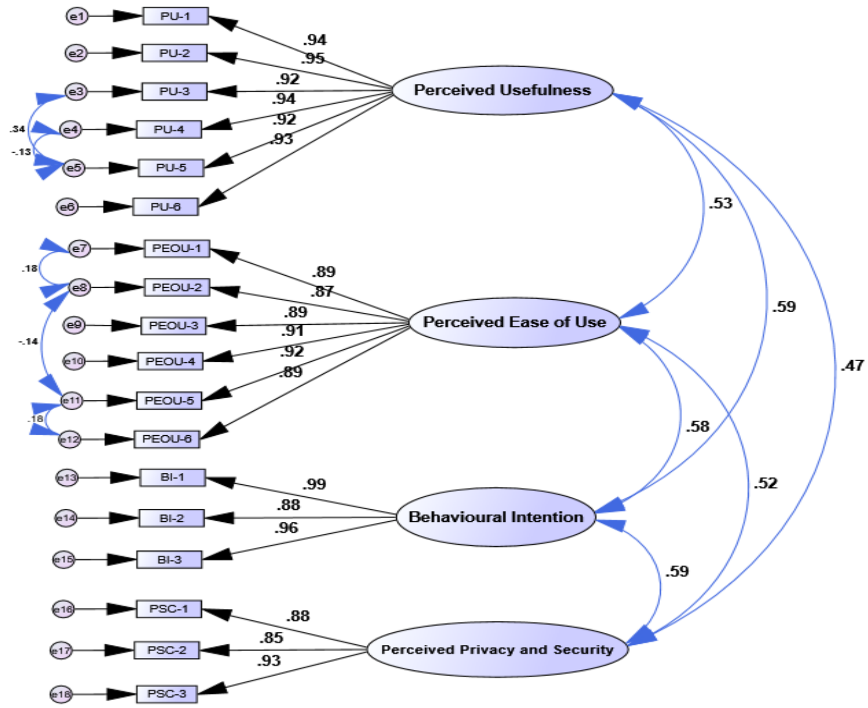

Fig. 3. The Measurement Model

Table 1
Goodness-of-Fit results (measurement model)

Fit index	Cut-off point	Achieved
Normed Chi-square (χ^2)	$0 \leq \chi^2/df \leq 2$	1.273
RMSEA	≤ 0.05	0.024
SRMR	≤ 0.05	0.0218
RMR	≤ 0.05	0.024
GFI	≥ 0.90	0.951
AGFI	≥ 0.90	0.942
NFI	≥ 0.90	0.976
NNFI (TLI)	≥ 0.95	0.987
CFI	≥ 0.95	0.972

5.2.1.2. Composite Reliability (CR)

It is widely agreed that CFA is preferable to Cronbach's alpha for estimating the composite reliabilities of the model components (Peterson & Kim, 2013; Boudlaie et al., 2022; Mukhlis et al., 2022; Mohammad et al., 2022). All constructs in the current research had CR coefficients above the threshold of 0.7 (Hair et al., 2018; Zahran et al., 2023; Pallathadka et al., 2023; Majdy et al., 2023), as shown in Table 2, showing strong levels of internal consistency.

Table 2
CR results

Factor	Items	
PU	6	0.943
PEOU	6	0.901
BI	3	0.922
PPS	3	0.963

5.2.1.3 Construct Validity

At this stage, the construct validity analysis was performed. Construct validity, according to Hair et al. (2018), may be measured using two kinds of measures: both convergent and discriminant validity.

5.2.1.3.1 Convergent validity

Convergent validity is the extent to which the observed variables on a given scale are related to each other. CR, average variance extracted (AVE), and standardized regression weights (SRW) results are usually used to evaluate convergent validity. In order to prove convergent validity, the following values are suggested: CR > 0.70, SRW > 0.70, and AVE > 0.50. (Hair et al., 2018; Dwijendra et al., 2023; AlBrakat et al., 2023).

The SRW and AVE results for all constructs are shown in Tables 3 and 4. Tables 2, 3, and 4 show that the findings indicate a good degree of convergent validity for all study's variables.

Table 3
Standardized regression weights (SRW)

Observed	Latent	SRW	Observed	Latent	SRW
PU-1	PU	0.938	PEOU-4	PEOU	0.915
PU-2	PU	0.953	PEOU-5	PEOU	0.917
PU-3	PU	0.916	PEOU-6	PEOU	0.890
PU-4	PU	0.943	BI-1	BI	0.986
PU-5	PU	0.923	BI-2	BI	0.882
PU-6	PU	0.932	BI-3	BI	0.963
PEOU-1	PEOU	0.888	PPS -1	PPS	0.879
PEOU-2	PEOU	0.875	PPS -2	PPS	0.855
PEOU-3	PEOU	0.892	PPS -3	PPS	0.928

Table 4
Average variance extracted AVE

Construct	AVE
PU	0.861
PEOU	0.824
BI	0.881
PPS	0.747

5.2.1.3.2 Discriminant Validity

Discriminant validity means that there is no high correlation between two sets of measures intended to evaluate different variables(Hair et al., 2018). Discriminant validity was determined by combining the AVE of each concept with its squared inter-construct correlations. The concept is considered to have discriminant validity if the inter-construct correlations are less than 0.85 and the AVE outputs are more than the squared inter-construct correlations for the same construct(Hair et al., 2018). Table 5 displays the discriminant validity findings. In the table, diagonal components reflect AVE values for each construct, inter-construct correlations are under the diagonal, and squared inter-construct correlations are above the diagonal. According to the data shown in Table 5, the inter-construct correlation coefficients were all less than 0.85. Additionally, each individual AVE score was higher than the corresponding squared inter-construct correlations. As a result, the analysis shows that all study constructs are discriminately valid.

Table 5
Discriminant validity results

Construct	PU	PEOU	BI	PPS
PU	0.861	0.271	0.356	0.207
PEOU	0.521	0.824	0.334	0.274
BI	0.597	0.578	0.881	0.355
PPS	0.455	0.524	0.596	0.747

5.2.2. The Structural Model: SEM

After confirming the composite reliability and construct validity of key constructs, the investigation shifted to examining the relationships between these constructs as outlined in the study's model.

5.2.2.1 The Structural Model Fit

Fig. 4 below depicts the construction of a structural model for additional SEM analysis. The structural model may be observed to include three endogenous variables (perceived usefulness, perceived ease of use, and behavioral intention) and one exogenous variable (perceived privacy and security). Following that, SEM using AMOS was used to assess the goodness-of-fit of the structural model output to the empirical data. As seen in Table 6, the findings reveal that the structural model offers a good overall match with the data.

Table 6
Goodness-of-Fit results (Structural Model)

Fit index	Cut-off point	Achieved	Fit index	Cut-off	Achieved
Chi-square (χ^2)	$0 \leq \chi^2 \leq$ 2df(2*124)	157.876	GFI	≥ 0.90	0.964
Normed Chi-square (χ^2)	$0 \leq \chi^2/df \leq 2$	1.266	AGFI	≥ 0.90	0.951
RMSEA	≤ 0.05	0.026	NFI	≥ 0.90	0.985
Associated p-close	≥ 0.5	1.000	NNFI (TLI)	≥ 0.95	0.996
SRMR	≤ 0.05	0.0227	CFI	≥ 0.95	0.997
RMR	≤ 0.05	0.030			

6. Hypothesis Testing

The research hypotheses were put to the test using the SEM output report once the structural model's goodness-of-fit had been successfully validated. Fig. 4 and Table 7 display the results, which demonstrate that each suggested causal path in the structural model was significant at the 0.001 level.In order to evaluate the final research model shown in Fig. 4 below explanatory power and gain better understanding of the nature of the interactions between its various components, Squared Multiple Correlations (SMC) for the model variables were collected. (Table 8 below). Based on Table 8 and Fig. 4, it is clear that PU, PEOU, and PS strongly predict BI, accounting for 51% of the variation in BI. Furthermore, the SMCs imply that, whereas PEOU and PS would explain 33.4% of the variation in PU, PPS would explain 26.8% of the variance in PEOU.

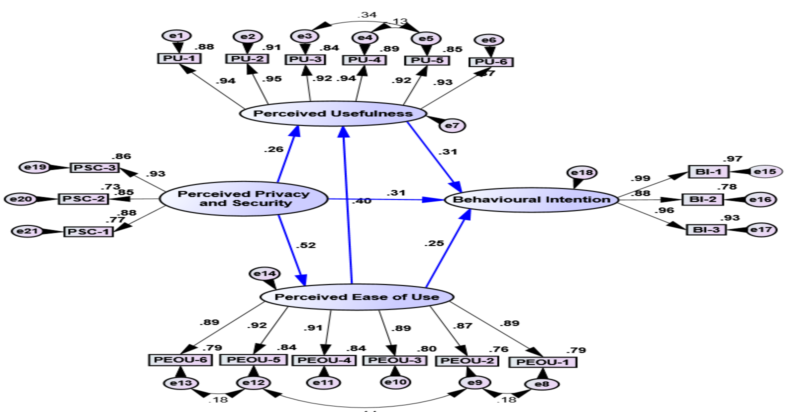

Fig. 4. The Structural Model

Table 7
Results of hypotheses testing

Hypothesis		Estimate	CR*	p-	Comment
Code	Path				
H1	PU → BI	0.290	7.123	***	Accepted
H2	PEOU → BI	0.214	5.567	***	Accepted
H3	PPS → BI	0.312	6.992		Accepted
H4	PEOU → PU	0.403	8.139	***	Accepted
H5	PPS → PU	0.276	5.334	***	Accepted
H6	PPS → PEOU	0.538	10.969		Accepted

*Cut off (CR >±1.96) (Hair et al., 2018)
*** p< 0.001

Table 8
Model predictive power

Factor	SMC
PU	0.334
BI	0.510
PEOU	0.268

7. Conclusion

Based mostly on Davis's (1989) TAM, a widely used model in the technology adoption literature, this research investigated the variables impacting managers' behavioral intention to utilize BDA in ICT SMEs in Jordan, as well as the causality relationships between these variables. CFA was employed to validate and verify the factor structure as well as examine construct validity and composite reliability for the components. In addition, SEM was applied to investigate the hypothesized causal associations between the various study variables. The dependent variable was behavioral intention to use BDA, which was assessed by three items (BI-1, BI-2, and BI-3). The CFA findings validated the expected underlying structure of this factor, as well as statistical evidence of its composite reliability and construct validity.

The perceived usefulness concept has a high composite reliability and a high rate of construct validity, according to CFA findings. In terms of PU's impact on BI, hypothesis testing found that the causal association between the two variables was significant at a level of p 0.001. As a result, the idea that PU favorably affects BI to use BDA is validated. As a result, PU is regarded as a crucial driver of managers' behavioral intentions toward implementing BDA. So, in order for BDA to be implemented in SMEs, managers' perceptions of its capacity to bring benefits in terms of productivity, performance, and profitability must be improved. Any such upgrade would have a beneficial impact on managers' behavioral intention to use BDA.

The results of the current research are in line with previous findings(Soon et al., 2016; Brock & Khan, 2017; Weerakkody et al., 2017; Shin & Bohlin, 2020; Surbakti et al., 2020). They show the importance of training and education programmes for BDA users in order to facilitate the approval and use of the system. Obviously, the more that users (managers) managers are convinced of its value to the firm, the more likely those users are to adopt the system.

The second hypothesis is supported by the findings of the SEM hypothesis testing (PEOU positively influences BI). Thus, the importance of PEOU in influencing managerial behavioral intention to use BDA is supported by empirical data. This suggests that if operators believe big data systems to be trouble-free or not requiring much effort, they will most likely adopt them (Shin and Bohlin, 2020). These findings also emphasize the importance of designing BDA to be user-friendly and easy to use (Soon et al., 2016; Weerakkody et al., 2017). In this respect, managers should search for easy-to-use and operate BDA systems and to ensure that they provide adequate training for employees in how to efficiently deal with related new technologies.

Hypothesis testing revealed that managers' concerns about privacy and security had a significant positive impact on BI. This finding suggests that the higher the managers' perception of BDA privacy and security, the greater their behavioral intention toward its adoption is likely to be. In other words, high security and privacy risk serves as an inhibitor to the implementation of BDA in businesses (Park & Kim, 2021). Many previous research studies have found that high privacy and security related risks negatively affect the diffusion of big data in organizations (Salleh and Janczewski 2019; Shahbaz et al., 2019).

Moreover, the results of this work clearly show that prior to introducing a BDA system, the organisation needs to communicate the simplicity and usefulness of the technology and promote organisational change to enhance learning and communication in order to guarantee the productive application of such a system.In order to motivate workers to adopt a BDA system and learn about its associated advantages, businesses should choose one that is simple to use and understand(Weerakkody et al., 2017; Shahbaz et al., 2019). Also, the current study findings revealed the significant influence of perceived privacy and security on both perceived ease of use and the perceived usefulness of the new technology.

Higher levels of perceived privacy and security are normally associated with lower levels of uncertainty in relation to the successful adoption of new technology (Grover, 1993).Therefore, in the BDA context, the need for privacy and security controls that are flexible enough to effectively address changing requirements will enhance managers' attitudes towards the technology's overall benefits as well as its usability (Salleh and Janczewski, 2019).

8. Directions for future research

With the addition of a new independent variable, namely perceived privacy and security, this research has effectively validated Davis's technological acceptance model. Regarding independent variables, the TAM has not been extensively examined in the perspective of big data. This study offers some key observations and research suggestions for the future, starting with the fact that it was conducted with Jordanian managers to give a window into attitudes in a developing economy. Hence, conducting a comparative analysis of BDA adoption in a similar economy could provide some useful insights.

Additionally, the research instrument was designed for first, middle, and top managers. As part of future research, that instrument could be adapted for use with the actual users of BDA applications, which would provide light on whether and how obtaining input from actual users vs management team makes a difference. Furthermore, although the current research model has the ability to offer useful insights concerning the use of BDA, Future research might focus on expanding its prediction performance by incorporating additional external aspects, such as: top management support, organizational readiness, social influence, competitive pressure, and government IT policies.

References

Adnan, K., & Akbar, R. (2019). An analytical study of information extraction from unstructured and multidimensional big data. *Journal of Big Data*, *6*(1), 1-38.

Ahsaan, S. U., & Mourya, A. K. (2019). Big data analytics: challenges and technologies. *Annals of the Faculty of Engineering Hunedoara*, *17*(4), 75-79.

Aityassine, F., Soumadi, M., Aldiabat, B., Al-Shorman, H., Akour, I., Alshurideh, M., & Al-Hawary, S. (2022). The effect of supply chain resilience on supply chain performance of chemical industrial companies. *Uncertain Supply Chain Management*, *10*(4), 1271-1278.

Ajimoko, O. J. (2018). Considerations for the Adoption of Cloud-based Big Data Analytics in Small Business Enterprises. *Electronic Journal of Information Systems Evaluation*, *21*(2), 63-79.

Al-Alwan, M., Al-Nawafah, S., Al-Shorman, H., Khrisat, F., Alathamneh, F., & Al-Hawary, S. (2022). The effect of big data on decision quality: Evidence from telecommunication industry. *International Journal of Data and Network Science*, *6*(3), 693-702.

Al-Azzam, M. K., & Alazzam, M. B. (2019). Smart city and smart-health framework, challenges and opportunities. *International Journal of Advanced Computer Science and Applications, 10*(2), 171-176.

Al-Azzam, M. K., Alazzam, M. B., & Al-Manasra, M. K. (2019). MHealth for decision making support: A case study of EHealth in the public sector. *International Journal of Advanced Computer Science and Applications*, *10*(5), 381-387.

AlBrakat, N., Al-Hawary, S., & Muflih, S. (2023). The effect of green supply chain on the export performance of the Jordanian pharmaceutical industry. *Uncertain Supply Chain Management*, *11*(2), 613-624.

Al-Hawary, S. I. S., & Obiadat, A. A. (2021). Does mobile marketing affect customer loyalty in Jordan?. *International Journal of Business Excellence*, *23*(2), 226-250.

Al-Nawafah, S., Al-Shorman, H., Aityassine, F., Khrisat, F., Hunitie, M., Mohammad, A., & Al-Hawary, S. (2022). The effect of supply chain management through social media on competitiveness of the private hospitals in Jordan. *Uncertain Supply Chain Management*, *10*(3), 737-746.

Alolayyan, M., Al-Qudah, M., Hunitie, M., Akour, I., Alneimat, S., Al-Hawary, S., & Alshurideh, M. (2022). Validating the operational flexibility dimensions in the medical service sectors. *Uncertain Supply Chain Management*, *10*(4), 1397-1404.

Al-Rwaidan, R., Aldossary, N., Eldahamsheh, M., Al-Azzam, M., Al-Quran, A., & Al-Hawary, S. (2023). The impact of cloud-based solutions on digital transformation of HR practices. *International Journal of Data and Network Science*, *7*(1), 83-90.

Alsghaier, H., Akour, M., Shehabat, I., & Aldiabat, S. (2017). The importance of Big Data Analytics in business: A Case study. *American Journal of Software Engineering and Applications*, 6(4), 111-115.

Alshawabkeh, R., AL-Awamleh, H., Alkhawaldeh, M., Kanaan, R., Al-Hawary, S., Mohammad, A., & Alkhawalda, R. (2022). The mediating role of supply chain management on the relationship between big data and supply chain performance using SCOR model. *Uncertain Supply Chain Management*, *10*(3), 729-736.

Al-Shormana, H., Alshawabkeh, R., Aldaihani, F., Aityassine, F., Mohammad, A., & Al-Hawary, S. (2021). Drivers of E-training Intention to Use in the private universities in Jordan. *International Journal of Data and Network Science*, *5*(4), 831–836.

AL-Tamimi, K. A., & Jaradat, M. S. (2019). The role of small medium enterprises in reducing the problem of unemployment in Jordan. *International Journal of Development and Economic Sustainability*, *7*(2), 28-36.

AL-Zyadat, A., Alsaraireh, J., Al-Husban, D., Al-Shorman, H., Mohammad, A., Alathamneh, F., & Al-Hawary, S. (2022). The effect of industry 4.0 on sustainability of industrial organizations in Jordan. *International Journal of Data and Network Science*, *6*(4), 1437-1446.

Arpaci, I., Yardimci Cetin, Y., & Turetken, O. (2015). Impact of perceived security on organizational adoption of smartphones. *Cyberpsychology, Behavior, and Social Networking*, *18*(10), 602-608.

Attiany, M., Al-kharabsheh, S., Abed-Qader, M., Al-Hawary, S., Mohammad, A., & Rahamneh, A. (2023). Barriers to adopt industry 4.0 in supply chains using interpretive structural modeling. *Uncertain Supply Chain Management*, *11*(1), 299-306.

Bayraktaroglu, S., Kahya, V., Atay, E., & Ilhan, H. (2019). Application of expanded technology acceptance model for enhancing the HRIS usage in SMEs. In*ternational Journal of Applied Management and Technology*, *18*(1), 48–66.

Boudlaie, H., Boghosian, A., Chandra, T., Al-Hawary, S. I. S., Hussein, R. A., Talib, S. G., ... & Iswanto, A. H. (2022). Investigating the effect of humility of Muslim leaders on the moral behaviours of followers and spirituality at work in Islamic society. *HTS Teologiese Studies/Theological Studies*, *78*(1), 6.

Brock, V., & Khan, H. U. (2017). Big data analytics: does organizational factor matters impact technology acceptance? *Journal of Big Data*, *4*(1), 1-28.

Broeders, D., Schrijvers, E., van der Sloot, B., van Brakel, R., de Hoog, J., & Ballin, E. H. (2017). Big Data and security policies: Towards a framework for regulating the phases of analytics and use of Big Data. *Computer Law & Security Review*, *33*(3), 309-323.

Bumblauskas, D., Nold, H., Bumblauskas, P., & Igou, A. (2017). Big data analytics: transforming data to action. *Business Process Management Journal*, *23*(3), 703-720.

Byrne, B. M. (2013). *Structural Equation Modelling with AMOS: Basic Concepts, Applications, and Programming*, Routledge.

Claes, V., Devriendt, E., Tournoy, J., & Milisen, K. (2015). Attitudes and perceptions of adults of 60 years and older towards in-home monitoring of the activities of daily living with contactless sensors: an explorative study. *International journal of nursing studies*, *52*(1), 134-148.

Coleman, S., Göb, R., Manco, G., Pievatolo, A., Tort-Martorell, X., & Reis, M. S. (2016). How can SMEs benefit from big data? Challenges and a path forward. *Quality and Reliability Engineering International*, *32*(6), 2151-2164.

Cui, F., Lin, D., & Qu, H. (2018). The impact of perceived security and consumer innovativeness on e-loyalty in online travel shopping. *Journal of Travel & Tourism Marketing*, *35*(6), 819-834.

Davis, F. (1989). Perceived usefulness, perceived ease of use, and user acceptance of IT. *MIS Quarterly*, *13*, 319–340.

Dubey, R., Gunasekaran, A., Childe, S. J., Wamba, S. F., & Papadopoulos, T. (2016). The impact of big data on world-class sustainable manufacturing. *The International Journal of Advanced Manufacturing Technology*, *84*(1-4), 631-645.

Dwijendra, N. K. A., Arsana, I. G. N. K., Al-Hawary, S. I. S., Prakaash, A. S., Parra, R. M. R., Jalil, A. T., & Hammid, A. T. (2023). Operation of the Multiple Energy System with Optimal Coordination of the Consumers in Energy Market. *Environmental and Climate Technologies*, *27*(1), 1-13.

Eldahamsheh, M.M., Almomani, H.M., Bani-Khaled, A.K.,Al-Quran, A.Z., Al-Hawary, S.I.S& Mohammad, A.A (2021). Factors Affecting Digital Marketing Success in Jordan. *International Journal of Entrepreneurship, 25*(S5), 1-12.

Félix, B. M., Tavares, E., & Cavalcante, N. W. F. (2018). Critical success factors for Big Data adoption in the virtual retail: Magazine Luiza case study. *Revista Brasileira de Gestão de Negócios*, *20*, 112-126.

Ferguson, A. G. (2016). *Policing predictive policing*. Wash. UL Rev., 94, 1109.

Field, A. (2018). *Discovering statistics using IBM SPSS statistics* (5th ed.). Thousand Oaks, CA: Sage.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, *18*(1), 39-50.

Grover, V. (1993). An empirically derived model for the adoption of customer-based inter-organizational systems. *Decision sciences*, *24*(3), 603-640.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2018). Multivariate data analysis (8th ed.). Boston: Cengage.

Halaweh, M., & Massry, A. E. (2015). Conceptual model for successful implementation of big data in organizations. *Journal of International Technology and Information Management*, *24*(2), 2.

Harahap, T. H., Dwijendra, N. K. A., Al-Hawary, S. I. S., Iswanto, A. H., Ahmed, N. M., Hasan, Y. M., ... & Mustafa, Y. F. (2022). A New Commodity Distribution Approach Based on Asymmetric Traveler Salesman Using Ant Colony Algorithm. *Industrial Engineering & Management Systems*, *21*(3), 538-546.

Hariri, R. H., Fredericks, E. M., & Bowers, K. M. (2019). Uncertainty in big data analytics: survey, opportunities, and challenges. *Journal of Big Data*, *6*(1), 1-16.

Hartono, E., Holsapple, C. W., Kim, K. Y., Na, K. S., & Simpson, J. T. (2014). Measuring perceived security in B2C electronic commerce website usage: A respecification and validation. *Decision support systems, 62*, 11-21.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural equation modeling: a multidisciplinary journal*, *6*(1), 1-55.

ITAJ: Information Technology Association-Jordan (int@j). (2018). 'ICT & ITES Industry Statistics & Yearbook'. Retrieved from: https://intaj.net/wp-content/Studies/2018.pdf

Jain, C. L. (2016). How to use big data and predictive analytics to improve the success of new products. *Review of Business*, 37, 48–55.

Jöreskog, K. G. & Sörbom, D. (1986). *LISREL VI: Analysis of Linear Structural Relationships by Maximum Likelihood, Instrumental Variables, and Least Squares Methods*, Mooresville, IN: Scientific Software.

Kache, F., & S. Seuring. (2017). Challenges and opportunities of digital information at the intersection of Big Data Analytics and supply chain management. *International Journal of Operations & Production Management*. 37 (1):10-36.

Khalayleh, M., & Al-Hawary, S. (2022). The impact of digital content of marketing mix on marketing performance: An experimental study at five-star hotels in Jordan. *International Journal of Data and Network Science*, *6*(4), 1023-1032.

Kobe, K., & Schwinn, R. (2018). Small business GDP 1998-2014. Office of Advocacy, US Small Business Administration: Washington, DC.

Kurdi, B., Alquqa, E., Alzoubi, H., Alshurideh, M., & Al-Hawary, S. (2023). The effect of process quality improvement and lean practices on competitive performance in the UAE healthcare industry. *Uncertain Supply Chain Management*, *11*(1), 261-266.

Lu, Y., & Xu, X. (2019). Cloud-based manufacturing equipment and big data analytics to enable on-demand manufacturing services. *Robotics and Computer-Integrated Manufacturing*, *57*, 92-102.

Majdy Amiruddin, M., Hamoud Alshahrani, S., Dwijendra, N. K., Shelash Al-Hawary, S. I., Turki Jalil, A., Muda, I., ... & Sunarsi, D. (2023). Religious behaviours and commitment among Muslim healthcare workers in Malaysia. *HTS Teologiese Studies/Theological Studies*, *79*(1), 8177.

Marolt, M., Zimmermann, H.-D., Žnidaršič, A., & Pucihar, A. (2020). Exploring social customer relationship management adoption in micro, small and medium-sized enterprises. *Journal of Theoretical and Applied Electronic Commerce Research*, *15*(2), 38-58.

Maroufkhani, P., Ismail, W. K. W., & Ghobakhloo, M. (2020). Big data analytics adoption model for small and medium enterprises. *Journal of Science and Technology Policy Management*, *11*, 483–513.

Mohammad, A., Aldmour, R., & Al-Hawary, S. (2022). Drivers of online food delivery orientation. *International Journal of Data and Network Science*, *6*(4), 1619-1624.

Mohammad, A.A.S (2019). Customers' electronic loyalty of banks working in Jordan: The effect of electronic customer relationship management. *International Journal of Scientific and Technology Research, 8*(2), 3809-3815.

Muda, I., Sivaraman, R., Al-Hawary, S. I. S., Rahardja, U., Bader, R. S., Kadarsyah, D., ... & Chaudhary, P. (2022). Hub Location-allocation in Computer-based Networks under Disruption Using Whale Optimization Algorithm. *Industrial Engineering & Management Systems*, *21*(3), 503-515.

Mukhlis, H., Al-Hawary, S. I. S., Linh, H. V., Hani, I. R., & Adnan, S. (2022). Religious capital and job engagement among Malaysian Muslim nurses during the COVID-19 pandemic. *HTS Teologiese Studies/Theological Studies*, *78*(1), 6.

Müller, S & P Jensen (2017). Big data in the Danish industry: Application and value creation. *Business Process Management Journal*, *23*(3), 645–670.

Nizam, T., & Hassan, S. I. (2017). Big data: A survey paper on big data innovation and its technology. *International Journal of Advanced Research in Computer Science*, *8*, 2173– 2177.

O'Donovan, P., Leahy, K., Bruton, K., & O'Sullivan, D. T. (2015). Big data in manufacturing: a systematic mapping study. *Journal of Big Data*, *2*(1), 1-22.

Ogbuokiri, B. O., Udanor, C. N., & Agu, M. N. (2015). Implementing big data analytics for small and medium enterprise (SME) regional growth. *IOSR Journal of Computer Engineering*, *17*(6), 35-43.

Olushola, T., & Abiola, J. O. (2017). The efficacy of technology acceptance model: A review of applicable theoretical models in information technology researches. *Journal of Research in Business and Management*, *4*(11), 70-83.

Pallathadka, H., Al-Hawary, S. I. S., Muda, I., Surahman, S. H., Al-Salami, A. A. A., & Nasimova, Z. (2023). The study of Islamic teachings in education: With an emphasis on behavioural gentleness. *HTS Teologiese Studies/Theological Studies*, *79*(1), 8193.

Park, J. H., & Kim, Y. B. (2021). Factors activating big data adoption by Korean firms. *Journal of Computer Information Systems*, 61(3), 285-293.

Peterson, R. A., & Kim, Y. (2013). On the relationship between coefficient alpha and composite reliability. *Journal of applied psychology*, *98*(1), 194-198.

Radhakrishnan, G. (2013). Non-experimental research designs: Amenable to nursing contexts. *Asian Journal of Nursing Education and Research*, *3*(1), 25-28.

Rahamneh, A., Alrawashdeh, S., Bawaneh, A., Alatyat, Z., Mohammad, A., & Al-Hawary, S. (2023). The effect of digital supply chain on lean manufacturing: A structural equation modelling approach. *Uncertain Supply Chain Management*, *11*(1), 391-402.

Razmak, J. & Bélanger, C. (2018), Using the technology acceptance model to predict patient attitude toward personal health records in regional communities, *Information Technology & People*, *31*(2), 306-326.

Salleh, K. A., & Janczewski, L. (2019). Security considerations in big data solutions adoption: Lessons from a case study on a banking institution. *Procedia Computer Science*, *164*, 168-176.

Schermelleh-Engel, K., Moosbrugger, H. & Müller, H. (2003). Evaluating the Fit of Structural Equation Models: Tests of Significance and Descriptive Goodness-of-Fit Measures. *Methods of Psychological Research Online*, *8*(2), 23-74.

Sebalj, D., Živković, A., & Hodak, K. (2016). Big data: Changes in data management. *Ekonomski vjesnik/Econviews-Review of Contemporary Business, Entrepreneurship and Economic Issues*, *29*(2), 487-499.

Shahbaz, M., Gao, C., Zhai, L., Shahzad, F., & Hu, Y. (2019). Investigating the adoption of big data analytics in healthcare: the moderating role of resistance to change. *Journal of Big Data*, *6*(1), 1-20.

Shin, D. H., & Bohlin, E. (2020). Demystifying big data: Anatomy of big data developmental process. *Telecommunications Policy, 40*, 837-854.

Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of Big Data challenges and analytical methods. *Journal of Business Research*, 70, 263-286.

Soon, K. W. K., Lee, C. A., & Boursier, P. (2016). A study of the determinants affecting adoption of big data using integrated Technology Acceptance Model (TAM) and diffusion of innovation (DOI) in Malaysia. *International journal of applied business and economic research*, *14*(1), 17-47.

Sun, S., Cegielski, C. G., Jia, L., & Hall, D. J. (2018). Understanding the factors affecting the organizational adoption of big data. *Journal of Computer Information Systems*, *58*(3), 193-203.

Surbakti, F. P. S., Wang, W., Indulska, M., & Sadiq, S. (2020). Factors influencing effective use of big data: A research framework. *Information & Management*, *57*(1), 103146.

Tao, F., Qi, Q., Liu, A., & Kusiak, A. (2018). Data-driven smart manufacturing. *Journal of Manufacturing Systems*, *48*, 157-169.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management science*, *46*(2), 186-204.

Verma, S. (2017). The adoption of big data services by manufacturing firms: an empirical investigation in India. *JISTEM-Journal of Information Systems and Technology Management*, *14*, 39-68.

Verma, S., Bhattacharyya, S. S., & Kumar, S. (2018). An extension of the technology acceptance model in the big data analytics system implementation environment. *Information Processing & Management*, *54*(5), 791-806.

Weerakkody, V., Kapoor, K., Balta, M. E., Irani, Z., & Dwivedi, Y. K. (2017). Factors influencing user acceptance of public sector big open data. *Production planning & control*, *28*(11-12), 891-905.

Yang, E., & Bayapu, I. (2020). Big data analytics and facilities management: A case study. *Facilities*, 38, 268–281.

Yudhistira, D. S., & Sushandoyo, D. (2018). Listening to the Voice of the Consumer: Expanding Technology Acceptance Model for Online Transportation Context. *The Asian Journal of Technology Management*, *11*(2), 125-136.

Zahran, B., Ayyoub, B., Abu-Ain, W., Hadi, W., & Al-Hawary, S. (2023). A fuzzy based model for rainfall prediction. *International Journal of Data and Network Science*, *7*(1), 97-106.

Zandieh, S. O., Yoon-Flannery, K., Kuperman, G. J., Langsam, D. J., Hyman, D., & Kaushal, R. (2008). Challenges to EHR implementation in electronic-versus paper-based office practices. *Journal of general internal medicine*, *23*(6), 755-761.