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A two-stage SEM-artificial neural network analysis of the organizational effects of Internet of things adoption in auditing firms

Awni Rawashdeh[a*], Layla Abaalkhail[b] and Mashael Bakhit[b]

[a]*College of Business, Applied Science Private University, Jordan*
[b]*Assistant Professor - Department of Accounting, College of Business Administration, Princess Nourah bint Abdulrahman University, Saudi Arabia*

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A B S T R A C T

This paper examines the role of vision as a mediating variable of the relationship between organizational factors and IoT adoption in audit firms in the US. Using a combination of analyses based on structural equation modeling (SEM) and artificial neural network (ANN) technology as the primary research methodology. Seven hypotheses were accepted, including one related to the impact of vision on IoT adoption. In general, all accepted hypotheses had a positive effect on IoT adoption. In addition to the direct positive impact of vision on IoT technology adoption, the magnitude of that effect varied depending on the context of each hypothesis. Drawing evidence from the results, this study demonstrates that vision was a partial mediating variable in the relationship between the organizational factor and IoT adoption. As a result, the model can help audit firms adopt IoT technology successfully. On the other hand, it makes essential recommendations for implementing IoT technology in light of the role that vision plays as a mediating variable in this model. The Technology-Organization-Environment (TOE) framework and Diffusion of Innovation theory (DOI) are combined with the vision to improve model predictive power.

1. Introduction

The emergence of the Internet of Things was accompanied by a keen desire to address the challenges facing audit firms with the support of management to achieve audit objectives through their ability to realize the value of knowledge. Zhou, Chong, & Ngai (2015) defined the Internet of Things as “a world where objects are connected, monitored, and optimized through wired, wireless, or hybrid systems”. The Internet of Things has received great academic attention since its emergence as a star in the business world, and many empirical studies have been conducted on the adoption of the IoT in various sectors, including the professions of accounting and auditing (Abed, 2020; Ahmetoglu, Che Cob, & Ali, 2022; Arnold & Voigt, 2019; Kumar et al., 2022; Tu, 2018). These studies have focused on the technological, organizational, and environmental aspects. These studies have found various factors affecting the adoption of the IoT. Despite this, the accounting profession differs from other companies in terms of the nature of its activities and objectives (Ernstberger, Koch, Schreiber, & Trompeter, 2020). Therefore, what may apply to other sectors may not necessarily apply to the sector of accounting and auditing firms. Moreover, studies in the context of accounting and auditing did not give sufficient depth to all the factors affecting the adoption of the IoT. Also, the studies that discussed adoption from an organizational perspective did not take into account variables such as absorptive capacity and willingness to face challenges; in addition to that, most of them ignored the role of the vision as a mediating variable or used an inappropriate variable. Most studies use intention as a mediating variable (Al-Momani, Mahmoud, & Ahmad, 2018), and it is recognized that the intention variable expresses intention at the level of the human individual (Chatterjee, 2022), who has emotions in the sense of intention and will (Anscombe, 2000). This means that the intention is influenced by emotions. Therefore, the study believes that the use of intent is not appropriate at the company level because there may be an employee in the same company who has the desire

* Corresponding author.
E-mail address: a_rawashdeh@asu.edu.jo (A. Rawashdeh)

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to adopt and the other does not, whichever represents the company's intention. The study believes that the company's vision can be used as an alternative to its intentions because it represents future goals that the company seeks to achieve, and in terms of a logical interpretation of things, these are intentions at the level of the company, not individuals. Therefore, vision is not subject to the logic of intention in individuals. Therefore, when asking the employee about the company's intention, there is no guarantee that the intention he expressed is the company's intention, unlike the vision that is written and placed in visible places. Therefore, it is necessary to conduct strong empirical research on the role of vision as a mediating variable in the relationship between organizational factors and IoT adoption in auditing firms. This study seeks to address this research gap. Therefore, the study investigated the role of vision in the relationship between organizational factors and IoT adoption, fearing that previous research had exaggerated the influence of organizational factors on IoT adoption without taking into account the role of the appropriate mediating variable. Several empirical studies have been conducted on the factors affecting IoT adoption (e.g., (Abed, 2020; Ahmetoglu et al., 2022; Arnold & Voigt, 2019; Kumar et al., 2022; Tu, 2018)) without considering vision. This shows how important it is to do solid research on IoT adoption and vision as a mediating variable in audit firms. This paper argues that the vision plays a mediating role in this study and is expected to influence the relationship between organizational factors and the adoption of the IoT, and thus the desire of audit firms to adopt the IoT and continue for the purposes of achieving audit objectives will be affected based on the importance of the role it will play. Vision as a mediating variable from the point of view of auditing firms. This is because the lack of a digital vision, for example, may lead to the company's unwillingness to adopt, either because of the company's inability to face challenges or its weak absorptive capacity and lack of support from management. As a result, the study investigated the impact of organizational factors on IoT adoption among auditing firms, while considering the mediating role of vision. Therefore, unlike previous studies that ignored the mediating role of vision, this study is expected to contribute to the literature and practices by testing new predictive variables, such as absorptive capacity and preparedness for challenges in the context of audit firms, in addition to verifying the role of vision as a mediating variable for intention.

2. Conceptual Framework

2.1 Technology-Organization-Environment (TOE) Framework

The literature suggests that two theories may serve as fundamental theoretic approaches for studying contextual factors of technology adoption. The first theory is the diffusion of innovation (DOI) theory, which provides the core technology for studying the spread of new technologies (Rogers, 1975, 1995a, 1995b). DOI theory postulates that innovation characteristics and organizational characteristics impact a company's adoption and use of innovations. The second theoretical approach is the technology-organization-environment (TOE) framework, which is directly developed from the DOI theory. The TOE framework highlights three factors (Bhattacharya & Wamba, 2018; Gangwar, Date, & Ramaswamy, 2015; Rosli, Yeow, & Siew, 2012a, 2012b) that might impact an organization's use of technology innovation: (1) the technological context describes the existing technologies and relevant technical skills available to an organization; (2) the organizational context refers to the internal measures of an organization such as top management; and (3) the environmental context is the external arena in which a company conducts its business – its industry, competitors, and trading partners (Tornatzky, Fleischer, & Chakrabarti, 1990). The TOE framework and the DOI theory coincide in several respects. For example, innovation characteristics in a technological context have similarities, and organizational characteristics in an organizational context also have similarities. Nevertheless, there are distinctions between the two theories. For example, in contrast to the DOI theory, the TOE framework does not assign significance to individual characteristics. Similarly, unlike the TOE framework, the DOI theory does not include the influence of environmental factors. In earlier studies on technology adoption, the importance of using TOE settings to improve the DOI theory has been well-established (AlSheibani, Cheung, & Messom, 2018; Amini & Bakri, 2015). In the literature, the TOE framework and DOI theory have often been used in various technology adoption domains, as does this study (Usman, Ahmad, & Zakaria, 2019). To achieve the study's objectives, the DOI was combined with the TOE framework. The TOE framework focuses on the environment, whereas the DOI theory focuses on innovation and organizational factors. As a result, the proposed model (Figure 1) should be able to explain the adoption of innovation within businesses (for example, audit firms) better and be complete. The TOE is also a popular framework in technology adoption research. It has been used in several IT adoption studies, including RFID (Bhattacharya & Wamba, 2018), AI (Alsheibani, Cheung, & Messom, 2018), blockchain (Upadhyay, Ayodele, Kumar, & Garza-Reyes, 2020), EDM (Musawa & Wahab, 2012), and auditing (Rosli et al., 2012b).

2.3 Predicting Factors Related to The Organizational Context

TOE framework takes into account adoption determinants originating within the adopting organization. These factors, which originate within the organization and then interact with the effects of technology, become a focal point for IoT technology adoption. As a result, this study examines three factors from an organizational standpoint: top management support, absorptive capacity, and preparedness for challenges.

2.3.1 Top Management support

According to Hsu, Liu, Tsou, and Chen (2019), top management support of technology adoption promotes service innovation. Arnold, Veile, and Voigt (2018) agree (Hsu et al., 2019) that technology adoption is significant. This requires top management support for successful deployment (Jaradat, Ababneh, Faqih, & Nusairat, 2020). Cortellazzo, Bruni, and Zampieri (2019) studied the importance of leadership in a digitalized environment. They found that leaders are crucial to the creation of a digital culture and can support innovation. Top management support is a significant predictor of cloud computing adoption, according to Priyadarshinee, Raut, Jha, and Gardas (2017). Siew, Rosli, and Yeow (2020) investigated audit firms' adoption of CAATTs and found top management support was significant. The adoption of IoT technology will have significant organizational ramifications and require significant investment. Arnold et al. (2018) say that IoT technology adoption requires top-level management support. According to Teo and Pian (2003), top management support is irrelevant to Internet adoption. The current study assumes a positive association between top management support and technology adoption, which remains true for IoT technology. Firms with top management support may be more amenable to utilizing IoT technology as a tool to collect additional supportive auditing evidence. Therefore, this study proposes the following hypothesis:

H$_1$: *Top management support has a direct positive influence on the IoT technology adoption.*
H$_2$: *Top management support has a direct positive influence on the IoT technology adoption via the vision.*

2.3.2 Absorptive capacity

Absorptive capacity is a company's ability to digest new knowledge and apply it to business goals (Cohen & Levinthal, 1990). Cohen and Levinthal (1990) stress the importance of absorptive capacity in innovation adoption. Absorptive capacity and technological adoption are linked by Sharma, Daniel, and Gray (2012). Absorptive capacity helps companies integrate complex technology (Sharma, Daniel, & Gray, 2012). Absorptive capacity is a key success criterion for IoT technology adoption since it delivers a new value paradigm for auditing businesses. Absorptive capacity has been studied as a technology adoption predictor. Wei, Lowry, and Seedorf (2015) found an association between absorptive capability and RFID usage in China. They claim that exposure to related technologies helps with novel technology adoption. Absorptive capacity influences BI system acceptance, according to Rouhani, Ashrafi, Ravasan, and Afshari (2018). Other research highlight absorptive capacity's importance (Cuevas-Vargas, Aguirre, & Parga-Montoya, 2022). While absorptive capacity has been used in many settings and studies, few have included it into IoT adoption models. Since IoT is a synthesis of modern auditing technologies, absorptive capability is audit companies' ability to recognize, analyze, and apply IoT to audit objectives. Audit organizations that know the latest IoT technologies and have the experience and skills to detect and use them are more likely to adopt IoT. This study proposes this hypothesis:

H$_3$: *Absorptive capacity has a direct positive influence on the IoT technology adoption.*
H$_4$: *Absorptive capacity has an indirect positive influence on the IoT technology adoption via the vision.*

2.2.2 Preparedness for challenges

According to challenge and response theory, a firm exposed to a challenge may respond negatively by being unprepared and excluding the idea or positively by accepting the challenge, acknowledging it, preparing for it, and then attempting to overcome it (Alberts, 2000). This preparedness may manifest through financial resources that facilitate technology adoption (Prause, 2019). Preparedness refers to a business's ability and willingness to adopt new technology (Savoia et al., 2012). Using previous definitions as a guide, preparedness for challenges can be defined as a positive prior response to challenges that enhances one's ability to accept, recognize, and prepare for the challenge. Brown (2010) indicated that preparation might take the form of training in response to the individual's discomfort when confronted with a new system or technology. Auditors face challenges in collecting supportive evidence, which necessitates the ability and expertise of the company to collect and improve data to extract appropriate audit evidence. As a result, audit firms are expected to provide technical support, including adequately qualifying auditors and securing a technological infrastructure that enables auditors to be adapted and internal and external evidence to be integrated into audit procedures. Therefore, preparedness for challenges has an expected relationship with adopting new technology. This study suggests that preparedness for challenges is significant for adopting IoT technology; thus, the following hypothesis was proposed:

H$_5$: *The preparedness for the challenge has a direct positive influence on the IoT technology adoption.*
H$_6$: *The preparedness for the challenge has an indirect positive influence on the IoT technology adoption via the vision.*

According to what was discussed in the introduction, the study assumes that vision acts as an alternative to intention in influencing the adoption of the IoT, so the following hypothesis is put forward:

H$_7$: *The vision has a direct positive influence on the IoT technology.*

3. Research Methodology

3.1 Targeted Survey on Facebook

The numerous advantages of probability sampling are well-known and well-proven. Among these advantages is the ability to generalize and extrapolate from samples (Schneider & Harknett, 2022). Notably, achieving this characteristic requires a sampling framework that accurately captures the target population without bias (Rawashdeh, Shehadeh, Rababah, & Al-Okdeh, 2022). There are no sampling frames for some hidden, remote, and difficult-to-reach populations, and probability sampling has never been an option, which has created some impetus for using tools to infer from non-probability sampling methods. Although the results obtained by this method may be no less significant than those obtained by probability sampling (Al-Rawashdeh, 2011), probability sampling has many advantages. To generalize and extrapolate to keep up with the technological revolution, it is necessary to develop alternative sampling techniques and data collection methods for potential respondents for whom probability sampling has historically and frequently been used (Schneider & Harknett, 2022). Due to low landline phone subscriptions, it is no longer possible to conduct telephone surveys in the same way, and the examination and banning of calls significantly affected response rates. As a result, the probabilistic samples are no longer probabilistic (Schneider & Harknett, 2022). This realization has led a new generation of survey researchers, including this study, to focus on the value of non-probability sample surveys (Goel, Obeng, & Rothschild, 2015; Schneider & Harknett, 2022; W. Wang, Rothschild, Goel, & Gelman, 2015). amples (Schneider & Harknett, 2022). Facebook has the most users, global coverage, the fewest subscription panels, and validates respondents' identities. Previous research used Facebook affinity group snowball sampling to collect surveys. Some studies (Brickman Bhutta, 2012; Facebook, 2022; Schneider & Harknett, 2022; Zagheni, Weber, & Gummadi, 2017) have used Facebook to create samples of the general population. Recently, demographers showed that Facebook's advertising platform could be used as a "digital statistic" to estimate immigrant numbers by country and US state (Zagheni et al., 2017).

The researcher can specify where the survey link should be displayed using the essential audience tool. After defining the potential respondents (target audience) broadly or precisely according to the study's objectives and selecting several criteria for precisely identifying potential respondents, the survey's appearance can be determined in any location specified by the researcher or in multiple locations. Additionally, the selection of potential respondents can be based on their age, gender, education, job title, and other characteristics. While the researcher can track the types of potential respondents reached by the survey, Facebook will never share personally identifiable information with potential respondents. Additionally, the researcher can include the interests of potential respondents whom the survey is expected to reach, such as checking the type of technology they prefer and constantly searching for and opening its links, which makes the survey more targeted and relevant to the study's subject.

Additionally, Facebook enables the researcher to target the survey based on the past browsing, viewing, or purchasing behaviors of potential study respondents. Additionally, it enables Facebook to target people connected to a specific Facebook page or event or exclude them from finding new potential respondents. Facebook enables the researcher to target potential respondents for the study in various ways. Additionally, Facebook allows targeting contact lists stored in a CRM system or email lists (Facebook, 2022). Lookalike audiences are a simple and potential way to connect with likely respondents to an online survey. Following the development of the target potential respondents, the survey links will then be distributed to potential respondents who share similar interests and characteristics.

As an advertiser, Facebook's audience targeting tools were used to buy ads and place the study link in a sponsored ad to target Facebook users who work for audit firms. Auditors of both sexes, men and women, were targeted with a university degree in auditing and accounting or a professional certificate in auditing or accounting. In addition, auditors between the ages of 21 and 70 interested in AI and IoT technology were targeted. Additionally, Facebook enables researchers to target respondents within a particular company or group of companies. The ability to target in this specific manner was a critical feature that enabled researchers to use their current data collection approach to achieve the campaign's aim. Notably, the feasibility of using targeted Facebook advertisements in the survey is contingent on Facebook offering targeting options that are relevant to the research topic. Facebook offers several options for audience targeting as part of a campaign. The default approach in this study, determined after consulting with Facebook's advertising specialists, is to set the campaign goal as “traffic”, which is equivalent to getting Facebook users to click on the link embedded in the ad that takes them to the online survey. Facebook's AI-based advertising algorithm translates these disparate objectives into a differential ad mode, a kind of black box that prevents the researcher from mapping the entire survey viewing process to the target respondent, which is a limitation of this approach. Additionally, because Facebook is a private company, it can change its rendering algorithm without prior notice or explanation, as it is an AI-based methodology that may bias the selected sample (Schneider & Harknett, 2022). Scholars have begun to respond to these calls in recent years, creatively utilizing data from sources such as Twitter, email, and Google searches to study migration, fertility, and other demographic processes (Billari, D'Amuri, & Marcucci, 2016; Brickman, Bhutta, 2012; Schneider & Harknett, 2022). Additionally, researchers conducted online surveys utilizing a variety of online nonprobability samples. These approaches are appealing partly because they can be implemented quickly and at a relatively low cost (Goel et al., 2015; Stern, Bilgen, & Dillman, 2014).

3.2 Measurement of The Factors

As previously stated, the TOE demonstrated the instrument's reliability and validity owing to the framework's adaptability and widespread application in several diverse studies. Additionally, the TOE validated the instrument's reliability and validity. The TOE framework and the DOI are combined in this study to provide a comprehensive model. The study model had three independent variables and vision as a mediating variable. Items from previous research measures were adapted to meet the requirements of this study. They were organized into a seven-point Likert scale ranging from "strongly disagree" to “strongly agree”, with “strongly disagree” being the most severe. The researcher structured the items in the form of a targeted online survey.

3.3. Sampling

Sampling as a reasonable sample frame reflecting all chartered accountants is neither readily available nor cost-effective for performing this research. As a result, the scope of this study was limited to a group of accountants who operate as qualified or chartered accountants and have academic qualifications as well as professional experience in auditing engagements in the US. Conditions (filters) are included in the questionnaire to assess whether or not this respondent fulfills the study sample's target sample criteria. This approach is viewed as being of great importance as it acts as a second corrective step in minimizing sample bias (Rawashdeh et al., 2022). In addition, the questionnaire features indicate whether or not a respondent is compatible with the study once he or she has chosen to participate (self-selection sample). It should be noted that by utilizing targeting tools accessible on the social networking site, the bias in the "self-selection sample" was reduced (Rawashdeh et al., 2022). These targeting tools were used to target a specific group of potential respondents with certain characteristics in the US, and then a filter was established using specific questions. For example, are you a certified public accountant or a chartered accountant? Do you work as an auditor for a company that performs audits? Do you work for audit firms? If the answer is affirmative, the questionnaire will be completed. If the answer to these questions is no, the survey will be ended with a thank you letter. With this approach, error can be kept to a bare minimum in a sample.

Oma (2016) asserts that neither a small sample nor a large sample is beneficial. According to Oma (2016), most research should use sample sizes greater than 30 but less than 500. Developing the ideas of Hair, Ortinau, and Harrison (2010), this study additionally utilized power analysis (G*Power) to calculate the appropriate sample size for the study at a confidence level of 95% (Input: Effect size $f^2 = 0.05$. α err prob = 0.05 Power (1-β err prob) = 0.95) in order to evaluate the data. The suggested sample size obtained from the G*Power is 402.Therefore, current study has sufficient data for analysis (671 responses). G*Power is a standalone power analysis application for numerous regularly used statistical tests (Faul, Erdfelder, Lang, & Buchner, 2007). According to the social networking site's audience targeting tool, the questionnaire's target audience is estimated to be 80,000 respondents, depending on the sample size conditions selected. The questionnaire received a 1.1 % click-through rate, averaging 671 responses, and 392 respondents completed the questionnaire, providing valid data for analysis. As a result, the ratio of those who completed questionnaires to respondents who opened the questionnaire was 58.4%, dividing 392 over 671. Although the percentage of people who see and click on the advertisement on social networking sites is small, the increased target audience compensates for the low response rate. Oma (2016) states that a sample size of 384 is necessary for a population size of one million. When the number of questionnaires clicked is compared to the recommendation of Oma (2016), the number of questionnaires obtained is expected to be appropriate.

4. Data Analysis

4.1 Model Fit Measure

The reliability of each item was determined by examining the cross-loadings. It was discovered that the factor loading values on their respective constructs were high, i.e., each factor loading was more than the 0.70 cut-off value (Table 1).

Table 1
Factor Analysis

Rotated Component Matrix[a]			
	Component		
	1	2	3
PC1	0.96		
PC2	0.96		
PC3	0.95		
PC4	0.93		
PC5	0.81		
AC1		0.96	
AC2		0.96	
AC3		0.95	
AC4		0.92	
AC5		0.75	
TMS1			0.97
TMS3			0.96
TMS2			0.96
TMS4			0.94
KMO and Bartlett's Test			
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.			0.88
Approx. Chi-Square			7046.38
df			91.00
Sig.			0.00

This also demonstrates the item's reliability and reinforces the item's allocation to the stated latent construct. Furthermore, it bolsters the case for convergent validity. In other words, if there is a shared variance between the constructs and the items (Blunch, 2012). The test outcomes were satisfactory, with eight variables with factor loadings ranging from 0.72 to 0.98 after rotation (Table 1). All of Cronbach's alpha values are above the frequently accepted threshold value of 0.70 (Taber, 2018). The results demonstrate that there are no cross-loads and, consequently, no items must be eliminated. The data was examined through factor analysis. As a result, the Kaiser-Meyer-Olkin (KMO) value is 0.86 (Table 1), above the advised 0.50 value, utilizing principal component analysis (PCAs) and varimax rotations (Kaiser, 1970). This study examined the convergent and discriminant validity of the structural model, and the hypotheses proposed by the model were examined using structural equation modeling (SEM) using AMOS 24, then using ANN model. Convergent validity is a measure of the degree to which various indicators of the same construct agree. To establish convergent validity (Table 2), one must examine the indicator's factor loading, composite reliability (CR), and average variance extracted (AVE) (Blunch, 2012). The value is between 0 and 1. The AVE value should be greater than 0.50 (Table 2) to ensure convergent validity (Blunch, 2012). According to Table 2, the CR for all constructs is greater than 0.70, while the AVE values range between 0.60 and 0.87 and are greater than 0.50. The discriminant validity of Fornell and Larcker (1981) was determined by comparing the square root of each AVE on the diagonal to the correlation coefficients (off-diagonal) for each construct in the relevant rows and columns. In general, there are no questions about the validity of this measurement (Table 2). The values in Table 2 indicate no discriminant validity problems according to the HTMT 0.85 criteria. This implies that the HTMT criterion refers to whether there are no collinearity problems among the latent constructs (multicollinearity). For example, the constructs of vendor support, management support, technology readiness, competitive pressure, and compatibility do not have problems. Each variable measures itself and does not overlap with other variables. In other words, it does not contain the overlapping items from the respondents' perception of the affected constructs, and there are no warnings for this HTMT analysis.

Table 2

Model Fit Measure

Measure	Estimate	Threshold							
CMIN	226.7	--							
DF	159	--		HTMT Analysis					
CMIN/DF	1.426	Between 1 and 3			1	2	3	4	5
CFI	0.993	>0.95		Challenges					
SRMR	0.041	<0.08		TopManagement	0.00				
RMSEA	0.033	<0.06		AbsorptiveCapacity	0.08	0.02			
PClose	0.999	>0.05		Vision	0.49	0.44	0.49		
TLI	0.993	Close to 1		IoTAdoption	0.55	0.44	0.51	0.79	
GFI	0.946	Close to 2							
Validity Analysis									
Validity	CR	AVE	MSV	MaxR(H)	1	2	3	4	5
Challenges	0.95	0.80	0.16	0.98	0.90				
TopManagement	0.96	0.87	0.11	0.97	-0.101*	0.93			
AbsorptiveCapac	0.95	0.80	0.27	0.98	-0.20***	-0.183***	0.90		
Vision	0.90	0.75	0.11	0.90	0.29***	0.335***	⁂	0.87	
IoTAdoption	0.82	0.60	0.27	0.86	0.39***	0.212***	0.52***	⁂	0.78

The researcher noticed that all the fit data in Table 2 indicated an ideal fit. The Chi-square value for the principal fit was 226.7, with a pClose of 0.999. 0.993 in terms of TLI; TLI ranges typically between 0 and 1. TLI values close to one indicate a good fit (Blunch, 2012; Hu & Bentler, 1999). The CFI (0.993) is identical to McDonald and Marsh (1990), except that it is trimmed to fall within the range of zero to one to estimate the model's non-centrality parameter. Near-1 CFI values indicate a great fit. In terms of SRMR, it is 0.041. The SRMR matrix differs from the model's observed and implied correlation matrix. As a result, it is possible to utilize the average magnitude of the actual and expected correlation discrepancies as an absolute measure of the (model) fit requirement. A value of less than or equal to 0.06 or 0.08 is a good fit. 0.033 as RMSEA is an absolute fit index that indicates how far a hypothesized model is from perfection. Also, an excellent fit for a root means a square error of less than 0.06.

4.2 Demographic Profile

Table 3 summarizes the survey respondents' demographics. The 31-40 age group received 55% of the 392 responses, making it the most significant response category, while the 20-30 age group received 26%. In terms of gender, males (53%) outnumbered females (47%) in the survey. All respondents had advanced degrees: 59% had bachelor's degrees, 13% had associate's degrees, and 7% had master's degrees.

Table 3

Demographic Information

Profile of the Respondent		Freq.	Percent	Profile of the companies		Freq.	Percent
Respondent Education	Bachelors	231	59%	Respondent Age	20-30 Years	102	26%
	Associate	51	13%		31-40 Years	216	55%
	Masters	27	7%		40+ years	74	19%
	High School	12	3%	Total		392	100%
	Other Degrees	71	18%	Respondent Experience	< 5 Years	86	22%
Total		392	100%		5-10	192	49%
Gender	Male	208	53%		10-15	59	15%
	Female	184	47%		>15	55	14%
Total		392	100%	Total		392	100%

4.3 Findings and discussions

To determine the statistical significance of estimated parameters derived from SEM, the Critical Value (CR) test statistic is used, which equals the parameter estimate divided by its standard error (SE). At a 0.05 level of significance, the CR (dividing the regression weight estimate (β) by the estimate of its standard error) value must be greater than 1.96. Any value less than this indicates that the parameter is unimportant for the model. All factors have a factor loading greater than or equal to +1.96, which is significant. According to Table 4, all of the study model's hypotheses are acceptable and have a statistically significant effect. The findings validated the study's hypothesis that vision acts as an alternative to intention in the suggested adoption model via the path of indirect influence.

Table 4
Regression Weights and Standardized Regression Weights

			Estimate	S.E.	C.R.	P	Beta
Vision	←	preparednessChallenges	0.268	0.017	15.368	***	0.516
Vision	←	TopManagementSupport	0.233	0.017	13.347	***	0.44
Vision	←	AbsorptiveCapacity	0.271	0.018	15.207	***	0.511
IoTAdoption	←	Vision	0.13	0.053	2.445	0.014	0.149
IoTAdoption	←	preparednessChallenges	0.239	0.02	12.114	***	0.527
IoTAdoption	←	TopManagementSupport	0.181	0.018	9.867	***	0.392
IoTAdoption	←	AbsorptiveCapacity	0.226	0.02	11.305	***	0.487

This study aimed to determine the factors that influence audit firms' adoption of IoT via vision as a mediating factor. As presented in Table 4, seven proposed hypotheses were supported. This study focused on measuring the impact of organizational factors on the adoption of IoT technology. In Table 4, H1 examined the effect of management support on IoT adoption directly. The findings indicate that top management support has a positive effect on the adoption of IoT technologies with beta weight (β = 0.392), and (C.R. = 9.867, P = 0.000). This refers to the fact that top management support facilitates the relationship between openness to technology and adoption. The effect of top management support on adopting IoT technology is consistent with findings from several previous studies (Cortellazzo et al., 2019). Similarly, the indirect effect (H2) of the top management support on adopting the IoT through the mediating variable represented by vision is also accepted by the beta coefficient (β = 0. 0.44) and (C.R.= 13.347, P = 0.000). Because top management decisions are inextricably linked to vision and competitive strategies, senior management support is critical in providing financial resources for the business while considering the consequences and risks associated with adopting and implementing the IoT. In Table 4, H3 examined the effect of absorptive capacity on IoT adoption directly. Findings revealed that absorptive capacity has a positive effect on IoT technology adoption with beta weight (β = 0.487) (Table 4) and (C.R.= 11.305, P = 0.000). This result indicates that the audit firms under study have the absorptive capacity related to recognizing the value of new knowledge, assimilating it, and applying it to business objectives because the firm's possession of the updated knowledge indicates that the company has experience in applying technology in addition to the ability to define duties and responsibilities related to implementing IoT technology. The effect of absorptive capacity on IoT technology adoption is consistent with some previous studies (Sharma et al., 2012). Likewise, the indirect effect (H4) of the absorptive capacity on adopting the IoT through the mediating variable represented by vision is also accepted by the beta coefficient (0.511) and (C.R.= 15.207, P = 0.000). This is because the company's vision stems from its ability to absorb knowledge related to technology. Table 4, H5 examined the effect of preparedness for challenges on IoT adoption. Findings revealed that preparedness for challenges has a positive effect on IoT technology adoption with beta weight (β = 0.527) (Table 4) and (C.R.= 12.114, P = 0.000). The hypothesis is accepted (Fig. 1).

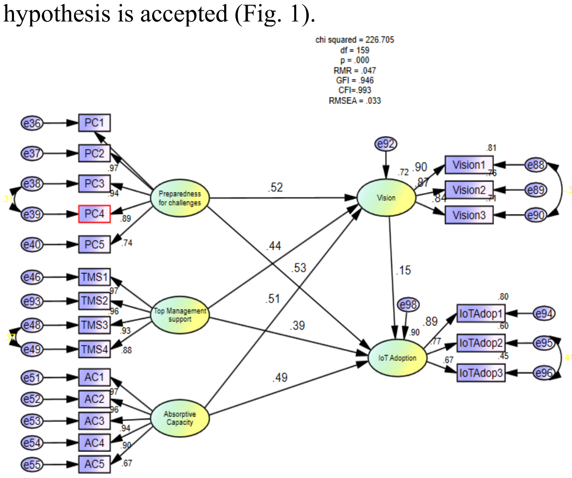


Fig. 1. Study Model

This result indicates that the audit firms under study can prepare for challenges through a positive prior response to challenges that enhances the firm's ability to recognize, accept, and prepare for the challenge. Likewise, the indirect effect of preparedness for challenges (H6) has an indirect effect on the adoption of the IoT through the intermediate variable represented by vision, which is also accepted with beta weight (β = 0.516) (Table 4) and (C.R.= 15.368, P = 0.000. This is because the vision is tantamount to future goals that it seeks to achieve and it is tantamount to preparation for the future and its challenges. The findings indicate that vision (H7) has a positive effect on IoT technology with beta weight (β = 0.149) and (C.R. = 2.445, P = 0.014).

4.2. Artificial Neural Network (ANN)

Haykin (2001) explains that an ANN is a massively parallel distributed processor composed of simple processing units that have a neural propensity for storing experimental knowledge and making it available for use and has been found to outperform conventional regression techniques. Artificial neural network (ANN) analysis was employed to validate the study's hypotheses. The multilayer perceptron (MLP) model identifies the influences of organizational factors on vision and IoT adoption (Fig. 2 and Fig. 3). The functions used to activate the hidden layer and output layer are hyperbolic, with data standardization serving as the resizing method for dependent and independent variables. Fig. 2 MLP model for identifying the influences of organizational factors on the vision. While, Fig. 3 MLP model for identifying the influences of organizational factors dimensions on the IoT adoption.

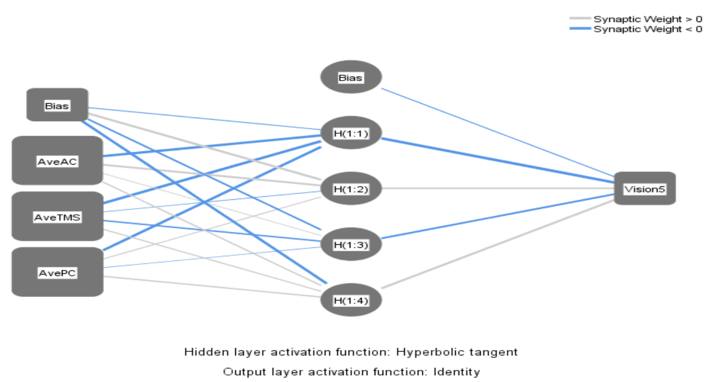


Fig. 2. MLP Model-Vision

Two ANN models were developed, vision and IoT adoption. The predictive accuracy of Models for Vision and IoT adoption was illustrated in Fig. 2. In this study, a Single-layer perceptron (SLP) was used to generate an artificial neural network (ANN) model with input (statistically relevant constructs to the study's exogenous variable), hidden, and output neurons, with the intention of enabling deeper learning for the output neuron node (Endogenous variables) (Ashaari, Singh, Abbasi, Amran, & Liebana-Cabanillas, 2021). A single-layer perceptron is a feed-forward network with a threshold transfer function. SLP is the simplest form of artificial neural network and can only classify situations with a binary target that is linearly separable (1, 0). In addition, both input and output neurons were normalized between [0, 1] in order to enhance the model's productivity. To prevent overfitting, a 10-fold cross-validation method with a 70:30 split between training and testing data was employed (Abbasi, Tiew, Tang, Goh, & Thurasamy, 2021; Ashaari et al., 2021). The root mean square of errors (RMSE) was suggested as a tool to further evaluate the correctness of the neural network model.

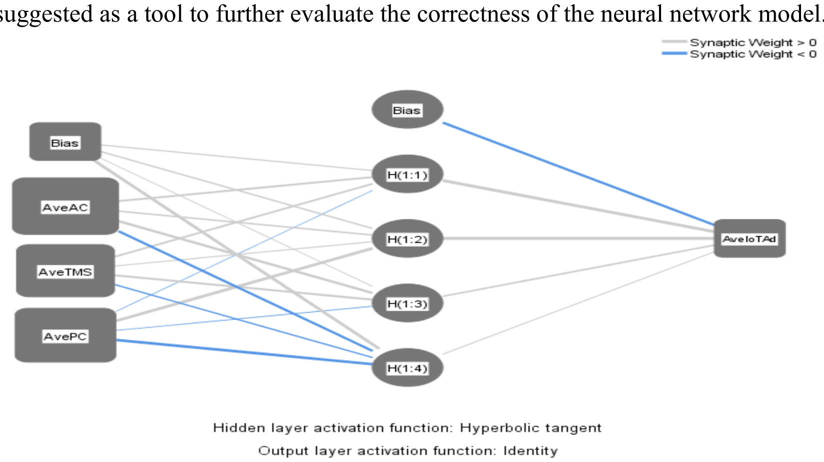
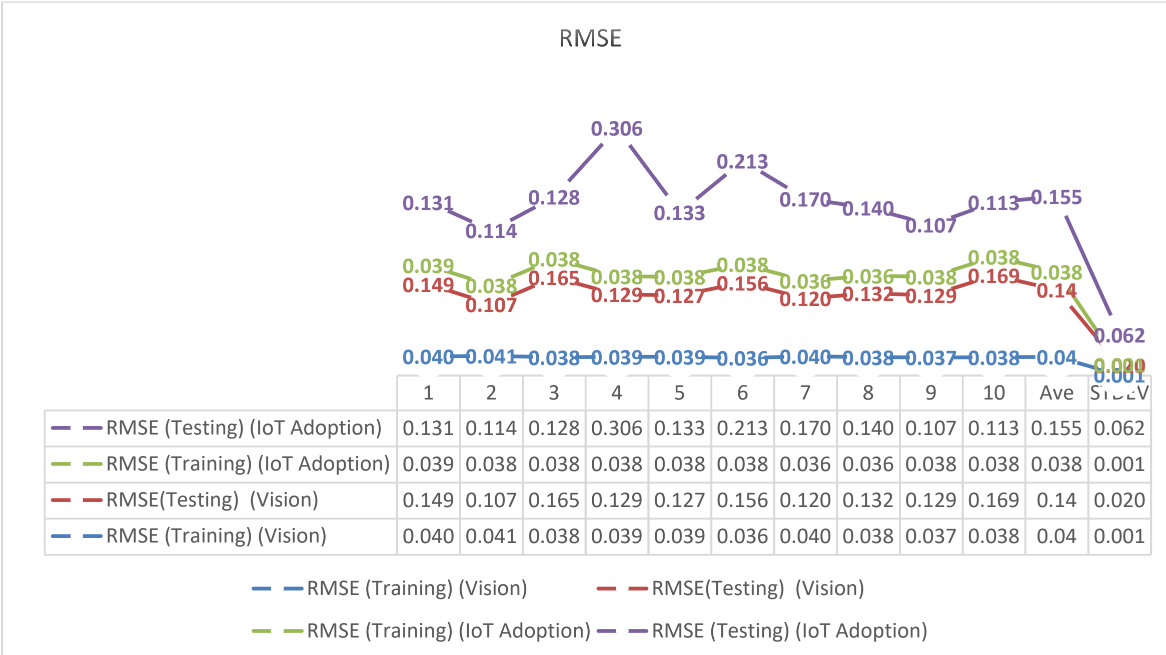


Fig. 3. MLP Model-IoT adoption

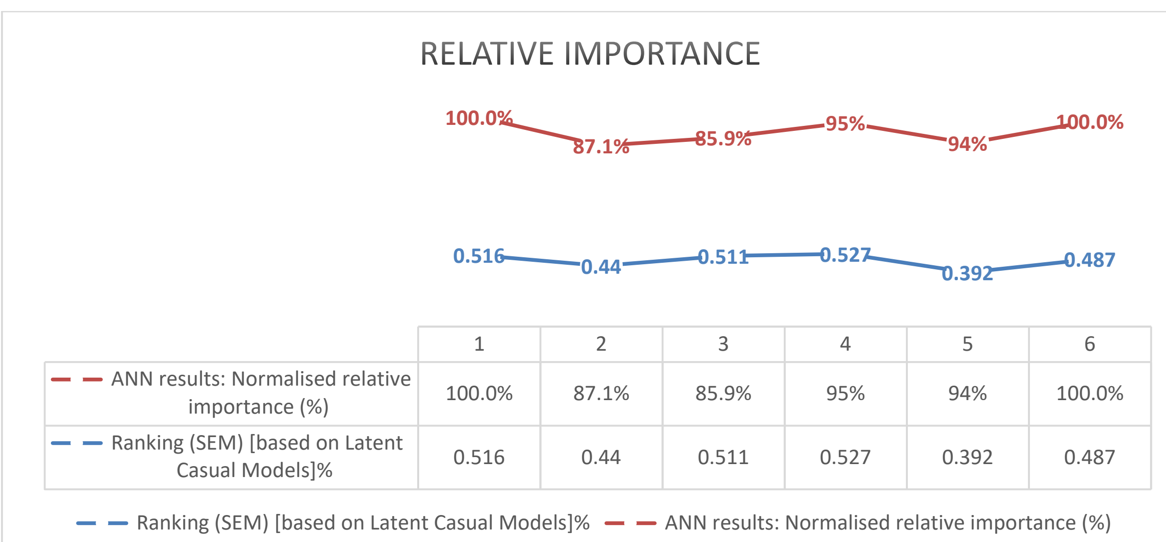
All of the mean values for RMSE (vision) for the training and testing phases ranged from 0.04 to 0.14, which are relatively small. Regarding the RMSE for IoT Adoption, all of the mean values for RMSE (IoT Adoption) for the training and testing phases ranged from 0.038 to 0.155, which are also relatively small. Thus, it can be concluded that ANN Models exhibit excellent predictive accuracy (Leong, Hew, Ooi, Lee, & Hew, 2019).



	1	2	3	4	5	6	7	8	9	10	Ave	STDEV
RMSE (Testing) (IoT Adoption)	0.131	0.114	0.128	0.306	0.133	0.213	0.170	0.140	0.107	0.113	0.155	0.062
RMSE (Training) (IoT Adoption)	0.039	0.038	0.038	0.038	0.038	0.038	0.036	0.036	0.038	0.038	0.038	0.001
RMSE(Testing) (Vision)	0.149	0.107	0.165	0.129	0.127	0.156	0.120	0.132	0.129	0.169	0.14	0.020
RMSE (Training) (Vision)	0.040	0.041	0.038	0.039	0.039	0.036	0.040	0.038	0.037	0.038	0.04	0.001

Fig. 4. The root mean square of errors (RMSE)

Next, a sensitivity analysis was performed to classify the external structures based on their normalized relative importance to the internal structures compared to the standardized estimates obtained from the SEM model. The figure shows a comparison of the variables in order of importance according to the ANN model and the latent-SEM model. Both the latent-SEM model and the ANN model produced similar results for all variables, as shown in the figure. Research conducted in two different stages permits a more precise and accurate analysis. First, SEM demonstrates the strength of the relationship between organizational factors, vision, and IoT adoption, while ANN describes the relationships between their components, general structures, and relative importance of factors. This confirms the importance of the variables that were included in the study model (Fig. 5).



	1	2	3	4	5	6
ANN results: Normalised relative importance (%)	100.0%	87.1%	85.9%	95%	94%	100.0%
Ranking (SEM) [based on Latent Casual Models]%	0.516	0.44	0.511	0.527	0.392	0.487

Fig. 5. Relative Importance

5. Conclusion

The findings demonstrate the factors affecting the adoption of IoT technology via vision as a mediating variable. This study developed a complete model incorporating the DOI, the TOE framework, and vision to ascertain the factors influencing IoT technology adoption in auditing firms in light of its passing on vision. The investigation's findings indicate that seven proposed hypotheses were accepted. The preparedness challenges associated with auditing firms' adoption of IoT technology were the most critical factor in the model. The findings of this study contribute to both theory and practice. The main contribution of this study toward theory is that it integrates various models with a vision to improve the knowledge of IoT adoption from the audit firm's perspective. Vision is essential, and it leads the audit firms' adoption of new technology such as IoT technology significantly. Although the TOE and DOI were frequently used in technology studies, few studies extended the TOE Framework using vision as a mediating variable, particularly in auditing firms. The other contribution is to empirically confirm the appropriateness of various factors (e.g., preparedness for challenges) and validate the holistic conceptual model in the context of audit firms. The study also confirmed the partial mediation of the vision in this proposed model. The study presents an academic contribution by integrating the TOE framework, DOI, and vision. It also contains a thorough literature analysis and an updated survey of IoT technology adoption in auditing firms. Additionally, the findings provide helpful insight for audit firm decision-makers. To begin with, top management support has a strong positive effect on IoT adoption. As a result, businesses considering implementing IoT technology in their operations must involve key decision-makers and assure adequate support. To ensure the sample selection was precise, the study also used a method of self-selection sampling. It reinforced it by targeting the study population precisely through tools for targeting audiences on social networking sites (Facebook) and including filters in the survey. Additionally, the targeting strategy increased the response rate and reduced the time required to gather data. However, this sampling method is non-probability, but it can be said to improve non-probability sampling, with the result being superior to the non-probability approach without improvement. In any case, this approach requires extensive examination to demonstrate its efficacy in future studies.

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