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THE RELATIONSHIP BETWEEN ARTIFICIAL INTELLIGENCE AND ENVIRONMENTAL DETERMINANTS IN AUDITING FIRMS

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Abstract

The purpose of this paper is to examine the effect of environmental factors on the adoption of IoT technology. A questionnaire was distributed to auditors via the targeting tools available on social networking sites in order to collect data on the technological factors affecting the adoption of artificial intelligence. The relationships between the variables were examined using structural equation modeling (SEM). Three hypotheses were accepted. In general, all accepted hypotheses had a positive impact on IoT adoption, but the magnitude of that effect varied depending on the context of each hypothesis. The model can help organizations adopt IoT technology successfully. On the other hand, it makes important recommendations for implementing IoT technology in big-four audit firms. The TOE framework is combined with the intention to improve model predictive power.

Keywords: TOE Framework, Internet of Things (IoT), Audit Firms, Commotion, Uncertainty, External Support

1. INTRODUCTION

Smart auditing enables flexible, real-time, and efficient data collection and analysis, resulting in an increase in auditing efficiency. While these benefits are associated with IoT technology, several studies have revealed disparities in terms of adoption intensity and extent (Bohli et al., 2015; Lee & Lee, 2015; Manyika et al., 2015). This study argues that environmental factors have an impact on IoT adoption. Consider previous research; similar findings apply to a variety of technologies, as businesses' technology adoption is contingent on a variety of determinants, each of which has a unique effect on IoT adoption. For example, (Caron et al., 2016) discussed the influence of IoT technology and its effect on individual privacy. Yang et al. (2021) investigate the factors influencing auditing firms' adoption of artificial intelligence. Ferri et al. (2020) examine the implementation factors that influence auditors' intentions to use blockchain technology in Big 4 accounting firms. Reyes et al. (2016) examine RFID adoption, while Pedrosa et al. (2019) investigate the determinants of CAAT auditing technology adoption. However, academic research on the most important factors that drive the adoption of IoT technology and how environmental factors affect IoT adoption from the point of view of auditing firms is scarce. Hence, the present paper aims to address this research gap by determining the factors that influence IoT technology adoption. By pursuing this aim, the study leads to increasing the limited research on IoT technology adoption from the auditing firms' perspective. Even though scholars have worked in this field for a long time, it is still a research area of high relevance and interest. Researchers predicted that by 2025, the total number of devices is expected to grow to 75 billion, according to Statista Research Department, or 80

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billion IoT devices (Gartner, 2017). Surveys for auditors will be conducted online using a targeting tool on social networking sites, and a filter was installed on the survey to increase the accuracy of the target sample. SEM was used to analyze the data.

2. PREDICTING FACTORS RELATED TO THE ENVIRONMENTAL CONTEXT

2.1TOE Framework

To answer the research question, the technology-organization-environment (TOE) framework of Tornatzky et al. (1990) is adapted. The TOE Framework serves as the framework for the study. The technology-organization-environment framework, also recognized as the TOE framework, is a conceptual framework that examines technology adoption in institutions. It also describes how the process of adopting and implementing technological innovations is influenced by the technological context, organizational context, and environmental context. In the year 1990, the model was first published by Tornatzky et al. (1990).

2.2 Competition

Rawashdeh et al. (2022) argue that competition is a good predictor of IT adoption. According to the study, audit firms are embracing advanced technology like the Internet of Things to expand their market share or recruit significant clients. Hallman et al. (2022) found that of competition is an important factor. In most studies, competition and technology adoption were linked. Zhu et al. (2003) argue, in keeping with the study's premise, that the adoption and implementation of new technology allow enterprises to alter the laws of competition and outperform competitors. The Big Four audit firms monopolize key clients. Big four and non-big-four firms compete. Competition drives faster adoption of innovative technology. Thus, simulation pressures develop as a result of competitive pressure, pushing the business to become more like other firms in the same sector (Cruz-Jesus et al., 2020). Businesses will replicate the actions of similar businesses in the same sector with similar goals. The corporation redesigns itself to seem like competitors to boost its profile without investing more in R&D. Simulation-related stress usually takes two forms. The first method is based on a competitor's repeated adoption of an innovation. Businesses try to copy others' best practices; a phenomenon called the "trailer effect." If many enterprises in the same sector adopt an invention, others would likely follow suit to avoid appearing less innovative or losing clients. This explanation implies that the corporation may use IoT technology due to comparable adoption by other audit firms. Second, competitors' successful innovation causes simulation stress. Under considerable uncertainty, firms adapt their competitors' best practices (Lee & Falahat, 2019). When competitors successfully deploy IoT technology, other clients may follow suit to avoid appearing less inventive to customers and to develop their client technology. The company may implement IoT technology to remain competitive, retain existing clients, and attract new clients. Simulation pressure affects artificial inelegance adoption, research shows (Ahmad & Mustafa, 2022; Al-Gasawneh et al., 2022). According to theory and research, competitors in a comparable business environment will pressure audit firms to implement IoT technology. This study proposes the following hypothesis:

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H1a. Competition has a direct positive influence on the intention of IoT technology adoption.

2.3 Uncertainty

IoT technology generates unstructured data in the form of videos, images, recorded phone calls, and sensors (Kumari et al., 2018). This raises significant ethical concerns about the confidentiality of audit clients (Wilson et al., 2017). Due to the lack of certainty on several fronts, clients may become hesitant to provide complete information to audit firms, impairing their ability to maintain the quality of their services. Additionally, when there is a shock to an auditor's reputation, firms with greater information doubt suffer the greatest losses (Billingsley & Schneller, 2009; Qasaimeh et al., 2022). As a result, this study suggests that when audit firms encounter uncertainty, they seek to adopt advanced technology that reassures their clients and motivates them to submit extra data obtained via IoT technology this means that uncertainty creates an incentive for audit firms to adopt. Patterson et al. (2003) believe that businesses confronted with high levels of uncertainty are more motivated to adopt advanced technologies. As a result, the following hypothesis is thus proposed by this study:

H2a. Environmental uncertainty has a direct positive influence on the intention of IoT technology adoption.

2.4 Perceived external support

The IoT technology aims to connect and integrate the physical and digital worlds. As such, the impact of external parties (such as business partners or, occasionally, governments) warrants special consideration (Bhattacharya & Wamba, 2018). Perceived external support can be defined as any effort undertaken by entities external to the enterprise that assists it in deciding whether or not to adopt IoT technology. Earlier research has demonstrated the importance of perceived external support for technology adoption (Bhattacharya & Wamba, 2018; Salleh & Janczewski, 2016). For example, Lee et al. (2017) examined the factors affecting RFID adoption in public and private organizations. The findings revealed that external support has a significant impact on RFID adoption in public and private organizations. Sunday and Vera (2018) similarly, an examination of information and communication technology (ICT) adoption in small and medium-sized enterprises (SMEs) revealed that external support has a significant positive effect on the successful implementation of ICT in small and medium-sized enterprises. Sunday and Vera (2018) discover a positive correlation between external expert consultations and mobile marketing technology adoption by service-based SMEs. Wibowo and Sari (2018) investigated ERP system adoption. Supplier actions were found to be a significant predictor of adoption in both trials. Rosli et al. (2012) stated that suppliers have an effect on the acceptance of computer-assisted auditing methods. As a result, the following hypothesis is thus proposed by this study:

H3a. Perceived external support has a direct positive influence on the intention of IoT technology adoption.

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3. SAMPLING

Sampling as a credible sample frame reflecting all chartered accountants is neither readily available nor cost-effective for performing this research (Rawashdeh et al., 2023). Consequently, the scope of this study was restricted to a group of chartered accountants who act as qualified or chartered accountants and have both academic credentials and professional experience in auditing engagements in their respective domains at audit firms. They are more likely to utilize IoT technology during the audit. For the aforementioned grounds, it can be stated that the study population is comprised of qualified and chartered accountants who are the focus of this investigation. It is crucial to improve the quality of non-probabilistic sampling methods and reduce current bias in light of the vast opportunities given by modern technological tools, notably audience targeting tools through their features. It was determined to use a self-selected sample (Bethlehem, 2016). Several modifications were performed in order to prevent bias in order to accomplish the research objectives. Initially, the intended respondents are targeted through the use of social networking site targeting tools, which help to ensure that the questionnaire link is distributed to the target sample in line with the questionnaire's targeting technique. The questionnaire includes conditions (filters) to determine whether or not the respondent meets the criteria for the study's target sample (Rawashdeh et al., 2022). As a second corrective step in the process of minimizing sample bias, this method is seen as being quite important. The characteristics of the questionnaire show a respondent's compatibility with the study once he or she has decided to participate (self-selection sample). It should be emphasized that the bias in the "self-selection sample" was reduced by applying targeting tools available on the social networking site. These targeting tools were used to target a certain group of potential respondents with particular characteristics, and then a filter based on specific questions was constructed. Are you a chartered accountant or a certified public accountant? Do you serve as an auditor for an organization that does audits? Do you work for accounting firms? If the response is affirmative, the questionnaire is filled out. If any of these questions are answered in the negative, the survey will conclude with a note of appreciation. With this method, bias in a sample can be kept to an absolute minimum.

4. DATA ANALYSIS

The CR (Critical Value) test statistic, which equals the parameter estimate divided by its standard error, is used to establish the statistical significance of estimated parameters generated from SEM (SE) (Rawashdeh et al., 2023; Rawashdeh et al., 2022). At a significance level of 0.05, the CR value must be greater than 1.96. Any value below this threshold implies that the parameter is irrelevant to the model. All of the factor loadings are more than or equal to 1.96, which is statistically significant. According to Table (1)'s findings, all of the study model's hypotheses are valid and have a statistically significant positive effect. This result is predictable given the objective of installing IoT technology. Indeed, this result is consistent with previous studies (Cruz-Jesus et al., 2020; Hsu et al., 2019; Kruse et al., 2019; Kumar & Shenbagaraman, 2017; Liao & Teng, 2017; Sunday & Vera, 2018; Wei et al., 2015), This shows that in the context of information technology usage, adoption intent can be deduced from environmental features. Recent empirical research has shown that the revised TOE framework typically

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excludes certain traits in favor of others, such as difficulties and compatibility. Future studies may consider employing this alternative methodology and/or enhancing the self-selected sample.

Table 1: Standardized Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P
IoT technology	<---	External Support	0.051	0.011		***
IoT technology	<---	Uncertainty	0.05	0.011	4.633	***
IoT technology	<---	Competition	0.07	0.01	6.662	***

Hu and Bentler (1999) suggest combining measurements, specifically CFI >0.95 and SRMR<0.08. To further solidify the evidence, this study obtained the RMSEA<0.06, 0.994 as GFI, 0.994 as NFI, 0.994 as CFI, 0.047 as SRMR, 1 as PClose, and 0.021as RMSEA. All of these figures very closely match the frequently proposed criteria (Blunch, 2012; Gaskin & Lim, 2016; Hu & Bentler, 1999).

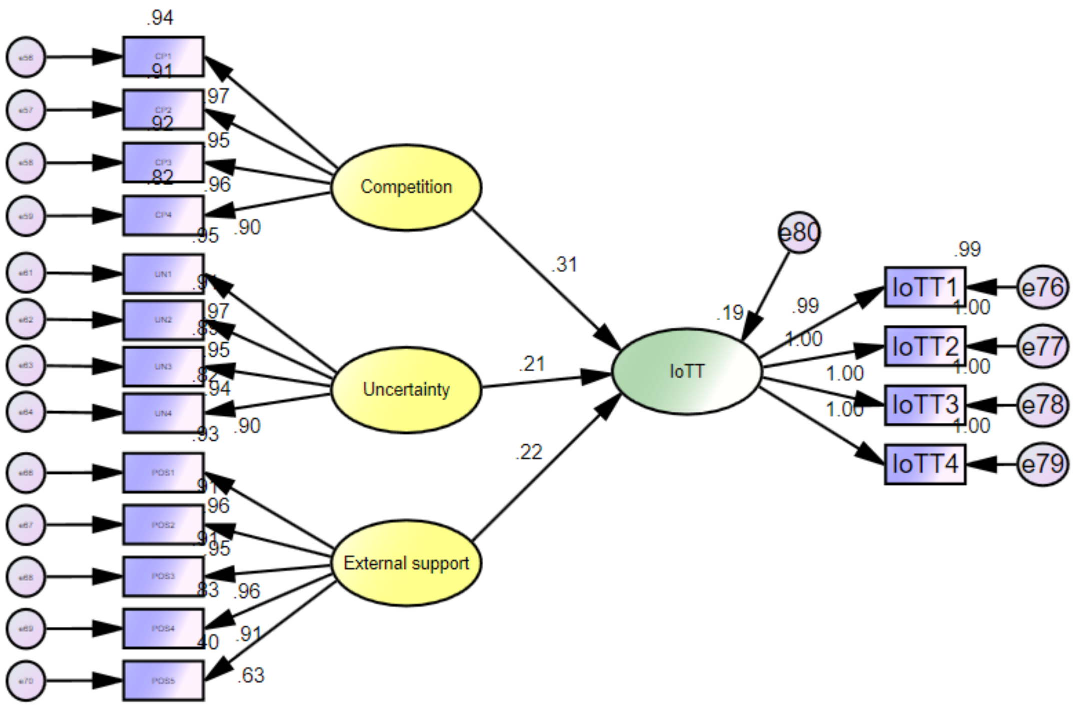

Figure 1: Study Model

This finding in Table 1 and Table 2 supported all hypotheses. Competition (C.R. =6.662) has a positive effect on the intent to adopt IoT technology (0.309). Uncertainty (C.R. =4.633) had a positive influence (0.21.4). Following that, External Support (C.R. =4.79) had a positive influence (0.222) on the intent to adopt IoT technology (Figure 1). This finding is consistent with those of other researchers.

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Table 2: Regression Weights: (Group number 1 - Default model)

IoT technology	<---	External Support	0.222
IoT technology	<---	Uncertainty	0.214
IoT technology	<---	Competition	0.309

5. CONCLUSION

In conclusion, the data suggest that environmental factors affecting have a major impact on IoT adoption. With the purpose of adopting IoT technology auditing organizations, this study created a model that combines the TOE framework. To ensure the method of the sample selection, the study additionally employed self-selection sampling and bolstered it by accurately targeting the study population via targeting tools on social networking sites and questionnaire filters. Unexpectedly, the targeting method also led to an increase in response rate and a reduction in the amount of time required to collect data. This sampling method is non-probability; however, it may be argued that it improves non-probability sampling, with the result being superior to the non-probability approach without improvement. In any event, future studies must be conducted to demonstrate the efficacy of this method. Future studies should take into account that audit firms of all sizes can utilize IoT technology.

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