Research Paper

International Journal of Research and Review
[Indexed, Peer-Reviewed Journal]
Volume 13; Issue: 6; June 2026
Website: www.ijrrjournal.com
E-ISSN: 2349-9788; P-ISSN: 2454-2237

Measuring e-Audit Readiness in the Banking Sector in Medan City: Perspective of Technology Readiness Index 2.0

Hendra Mulnandar[1], Sambas Ade Kesuma[2], Rina Br. Bukit[3]

[1,2,3]Department of Accounting, Faculty of Economics and Business Universitas Sumatera Utara, Indonesia

Corresponding Author: Hendra Mulnandar

DOI: https://doi.org/10.52403/ijrr.20260629

ABSTRACT

The purpose of this study was to measure the readiness of banking personnel, particularly internal auditors, to adopt e-Audit in their daily work. Data were obtained from divisions relevant to e-Audit, including the main division and the system's supporting divisions. This study successfully collected data from 175 respondents from 11 banks, including all state-owned banks, several large private banks, and one of the largest regional banks owned by the local government in Medan. The data analysis techniques used were descriptive analysis in IBM SPSS and the Partial Least Squares Structural Equation Model with SmartPLS.
The results showed that, in an organizational context, OPT and DIS significantly influence e-Audit Readiness. Meanwhile, INN and INS did not. Furthermore, DIS had the strongest influence on e-Audit Readiness. Conversely, INS had the weakest influence on e-Audit Readiness. These findings provide empirical support for the TRI 2.0 instrument in the e-Audit context and confirm the validity and reliability of the TRI scale used.

Keywords: e-Audit Readiness, Optimism, Innovativeness, Insecurity, Discomfort, System Adoption in Organizations, Local Banking in Medan

INTRODUCTION

Throughout 2023, various large companies promoted the use of emerging technologies, with many investing heavily in Artificial Intelligence (AI) (Fortune, 2024). The digital transformation has also encouraged the conduct of audit activities with the assistance of technology, known as Electronic Audits (e-Audit). The use of e-Audit has occurred in various fields, including the use of technology in the context of social and environmental audits in the production chain (Castka et al., 2020). Furthermore, technology has been utilized in construction compliance audits (Beach et al., 2024). In the context of environmental audits, the latest technology is also used to measure emission levels of certain substances (Gu et al., 2023). In the financial sector, the latest technology has been adopted in accounting and auditing activities (Munoko et al., 2020).
Across the world, recent developments in e-Audit include the use of blockchain technology by the Big Four public accounting firms based in Europe and the United States to improve the quality of client e-Audit. The Big Four public accounting firms include Klynveld, Peat, Marwick, Goerdeler (KPMG, 2023); Pricewaterhousecoopers (PwC, 2024); Deloitte (2023); and Ernst & Young (2020). In the UK, the use of e-Audit has expanded in the public healthcare sector (Begkos et al., 2024). One example of e-Audit in the

environmental context is the use of satellite imagery and sensors to measure methane emissions from oil and gas companies in Texas and New Mexico (Gu et al., 2023).

In Asia, particularly in China, there have been several phases of e-audit implementation. The China National Audit Office (CNAO) successfully developed an e-audit project called the Jin Shen Project (Chen et al., 2012). Then, organizations and companies in China began exploring AI, introducing the first financial robots to perform various auditing tasks (Bai, 2017). Currently, public accounting firms and all companies listed on the Chenzen and Shanghai stock exchanges have adopted AI in accounting and auditing contexts (Rahman et al., 2024).

Elsewhere in Asia, some industrial companies listed on the Jordanian stock exchange have used cloud-based technology to support internal auditors (Alqudah et al., 2024). Some external and internal auditors in Jordan and Egypt have also implemented data mining in their accounting and auditing (Almaqtari et al., 2024).

In Southeast Asian countries, some external auditors in Vietnam in Hanoi and Ho Chi Minh City are currently using the latest technology, namely Interactive Data Extraction and Analysis (IDEA) software for data import and analysis, Power Business Intelligence (Power BI) for data visualization, Robotic Process Automation (RPA) for transaction processing, and Drones and Radio Frequency Identification (RFID) for inventory audits (Nguyen et al., 2024).

In Indonesia, several institutions have implemented e-Audit, including the Ministry of Environment and Forestry (KLHK), which has used e-Audit to facilitate auditors' data verification through software (KLHK, 2020). Then, in 2023, the Financial Services Authority (OJK) encouraged internal auditors in the financial services sector to use the latest e-Audit technology to assist them in their duties more effectively and efficiently (OJK, 2023). Most recently, the Government Goods and Services Procurement Agency (LKPP) adopted e-Audit in 2024 by publishing an electronic catalog accessible to the Government Internal Supervisory Apparatus (LKPP, 2024).

Furthermore, one important factor is measuring e-Audit in terms of user readiness, or e-Audit Readiness. It is because the level of technological readiness among Indonesian is still relatively low compared to other Southeast Asian countries. According to Katadata's databox (2023), Cisco, a US-based agency, ranked Singapore first with a score of 2.37 points. Then, Malaysia (0.46 points), Thailand (0.32 points), and Vietnam (0.22 points). Indonesia is next in fifth place with a score of -0.06 points, followed by the Philippines (-0.25 points) and Cambodia (-0.38 points). Next, Timor Leste (-0.8 points), Myanmar (-0.85 points), and Laos (-0.89 points). The following is a summary of the explanation above in a graph.

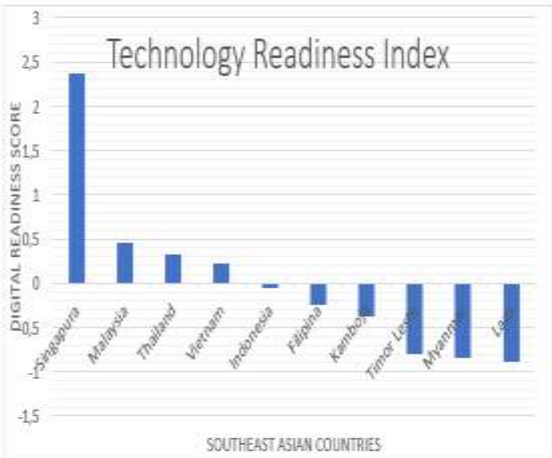

Figure 1. Technology Readiness Index of Countries in Southeast Asia

Source: databoks katadata, 2023

Furthermore, the banking sector is one organization whose e-Audit Readiness needs to be measured. It is based on research by Hamza et al. (2023), which found that using e-Audit can improve banking financial performance. Furthermore, e-Audit using Data Analytics (DA) in banking can improve the quality of audit decision-making in banking (Kamdjoug et al., 2024). Furthermore, several e-Audit elements, including Enterprise Resources Planner

(ERP), Extensible Business Reporting Language (XBRL), and DA in banking, facilitate the audit process for high-risk accounts (Gambetta et al., 2016).

Therefore, to measure e-Audit Readiness in banking, a technology readiness theory is used. One theory for measuring technology readiness is the Technology Readiness Index 2.0 (TRI 2.0) by Parasuraman and Colby (2015). This theory is used to measure an individual's readiness to face and use the latest technology to complete various tasks in both personal and organizational contexts (Parasuraman & Colby, 2015). In TRI 2.0, various human psychological factors are considered in combination, including both supportive and inhibiting psychological conditions related to the use of the latest technology (Parasuraman & Colby, 2015). The TRI 2.0 theory includes four benchmark variables: Optimism (OPT), an individual's positive perspective on technology, and the belief that technology can foster greater human control (Parasuraman & Colby, 2015). Innovativeness (INN) refers to an individual's perceived tendency to be a pioneer and leader in technology (Parasuraman & Colby, 2015).

Next, Discomfort (DIS) refers to an individual's perceived inability to control technology and a feeling of being controlled by it (Parasuraman & Colby, 2015). Finally, Insecurity (INS) refers to an individual's lack of confidence in technology and doubts about its ability to create added value (Parasuraman & Colby, 2015). The advantages of TRI 2.0 compared to TRI 1.0 are that TRI 2.0 is more concise and various improvements in the index make TRI 2.0 more robust for use in various contexts and over time (Parasuraman & Colby, 2015).

The TRI also offers several advantages over other theories because it focuses not only on individual motivation but also on the individual's readiness, measured by positive and negative mental aspects of technology use (Flavian et al., 2021). The TRI can also classify individuals into technology users and non-users, differentiate users based on positive and negative beliefs, and identify users with significant feelings of insecurity and discomfort (Florestiyanto, 2015). Furthermore, the TRI includes a psychological scale that helps companies understand stakeholders' technology readiness, including customers and employees, particularly regarding the use of computers and internet-based technologies (Parasuraman, 2000).

From the background explanation above, it can be concluded that the use of e-Audit has grown globally, in both financial and non-financial contexts. Specifically in the financial sector, the Big Four Public Accounting Firms, including PwC, EY, Deloitte, and KMPG, have offered the latest technology to improve client e-Audit performance. In Asia, the use of the latest technology has been used in the context of internal and external audits in several countries, including China, Jordan, Egypt, Vietnam, and Indonesia.

However, there is a gap in practice in adopting the latest technology for audit activities. Research by Erişen and Erer (2023) found that some internal auditors at various companies in Turkey expressed doubts about the use of the latest technology to assist their audit work.

Furthermore, in using TRI 2.0, several different results were found that measure individual readiness for the latest technology. Research by Flavian et al. (2021), Tu et al. (2023), and O'Hern and Louis (2023) showed that the variables Optimism (OPT) and Insecurity (INS) had significant effects on Technology Readiness (TR). Conversely, Yosser et al. (2020) found that only the Insecurity (INS) variable had a significant effect on TR. Research by Etim and Daramola (2023) and Kaushik and Agrawal (2021) found that the variables OPT, INN, INS, and DIS were not significant for TR. Conversely, research by Alhammadi et al. (2023), Ozel et al. (2023), Elvis and Kim (2022), and Cimbaljevic et al. (2023) found that all four variables—OPT, INN, INS, and DIS—were significant on TR.

Other gap studies include Shariffuddin et al.

(2023), which found that only the Innovativeness (INN) variable was significant for TR, while Liljander et al. (2006) found that only the OPT (Organizational Operational Change) variable was significant for TR. Qasem's (2021) study found that both OPT and INN variables were significant for TR. Furthermore, Huy et al. (2019) found that OPT, INS, and DIS variables were significant for TR, while Dharma et al. (2017) found that only DIS variables were significant for TR.

This research was conducted in the banking sector in Medan City, the third-largest city in Indonesia. Therefore, banking activities in Medan are considered representative of those conducted at its headquarters in Jakarta. Another reason for this research is the similarity of domicile, which facilitated the research process. Considering the still minimal use of TRI to measure e-Audit readiness, this prompted the research, namely "Measuring e-Audit Readiness in the Banking Sector in Medan City with the Perception of Technology Readiness Index 2.0".

LITERATURE REVIEW

Electronic Audit (e-Audit)

e-Audit is an activity in accounting and auditing that uses technology, enabling companies to control the audit process and make it more effective and efficient (Custard, 2024).

According to Dai and Vasarhelyi (2016), there are several phases in e-Audit, including:

1. Audit 1.0, an audit conducted using paper, pencil, and calculator.
2. Audit 2.0, an audit conducted using software applications such as Microsoft Excel and Computer Assisted Audit Techniques (CAAT).
3. Audit 3.0, an audit conducted with large data sets using DA applications.
4. Audit 4.0, an audit based on the latest technology, which automates audit activities using cloud servers, AI, blockchain, and the like.

The definition of e-Audit Readiness in this study is the level of organizational capability in human resources, technology, and procedures for implementing technology-based audits. One key aspect of e-Audit Readiness that is re-emphasized is the organization's Human Resources (HR) readiness (Zolila, 2024). Several criteria for measuring HR readiness for e-Audit include technical competence, understanding of the e-Audit process, attitudes and perceptions regarding e-Audit, training and development, regulatory compliance, HR availability, and managerial support (Adepoju, 2022; PwC, 2023).

In this study, the focus of measuring HR readiness for e-Audit Readiness is the attitudes and perceptions of organizational HR towards the use of e-Audit. Furthermore, to measure HR attitudes and perceptions regarding the use of e-Audit, the four TRI 2.0 variables are used: OPT, INN, INS, and DIS.

Optimism (OPT)

In technological readiness, the OPT variable measures the extent to which individuals perceive a new technology positively (Parasuraman, 2000). This variable reflects individuals' perceptions that technology can increase flexibility, effectiveness, and control (Parasuraman, 2000). When individuals feel optimistic about technology, they are more likely to invest in the latest technology, potentially making them feel more empowered by it (Oh et al., 2014).

According to Parasuraman and Colby (2015), the OPT variable consists of four indicators that measure positive views and beliefs that technology can improve flexibility, efficiency, and quality in work. These four indicators measure perceptions of improved job quality, mobility, control, and productivity due to technology.

Innovativeness (INN)

The INN variable measures the extent to which individuals desire to be pioneers in new technologies and become leaders in

those technologies (Parasuraman, 2000). The OPT and INN variables complement each other in individuals' acceptance of new technologies, with those who are more motivated to be pioneers in technology holding a more positive view of the new technology (Parasuraman, 2000). The INN variable does not involve internal factors in the readiness to use the latest technology (Agarwal & Prasad, 1998).
Furthermore, the INN variable has four indicators that measure the tendency to be a technology pioneer (Parasuraman & Colby, 2015). These four indicators measure the perceived tendency of others to seek advice on new technologies, to use new technologies when they become available, to understand new technologies without assistance, and to stay abreast of new technological developments.

Insecurity (INS)
Regarding the technological readiness factor, Parasuraman (2000) stated that the INS variable reflects uncertainty about technology and doubts about whether technology can improve work. Parasuraman (2000) also stated that the INS variable is among those that inhibit individuals from trying new technologies. Lin et al. (2007) stated that the INS variable influences users' risk perceptions when adopting new technologies, which in turn influences their intention to use them, even though the technology has proven to have real benefits.
According to Parasuraman and Colby (2015), the INS variable has four indicators that measure doubts about technology use and concerns about its potential negative impacts. These four indicators measure individuals' perceptions of high dependence on technology, excessive negative impacts of technology use, declining quality of interpersonal relationships due to technology, and decreased security due to technology.

Discomfort (DIS)
Another variable in the TRI that inhibits technological readiness is DIS. The DIS variable reflects perceptions of a lack of control over technology and of difficulty in using it (Parasuraman, 2000). According to Lin et al. (2007), one factor influencing an individual's intention to use electronic services is the DIS variable.
Parasuraman and Colby (2001) stated that the DIS variable is used to measure the extent to which individuals feel burdened by technology due to a lack of ability to use it effectively. According to them, there are differences between the DIS and INS variables in terms of technology barriers. The DIS variable emphasizes the technical aspects of technology, while the INS variable emphasizes its security aspects.
Parasuraman and Colby (2015) stated that the DIS variable has four indicators that measure perceptions of a lack of ability to understand new technology and of perceived difficulty in using it. These four indicators measure perceptions that technical service providers take advantage of users, cannot explain what is needed, are not designed for ordinary people, and offer no guides written in simple language about new technology.

Framework

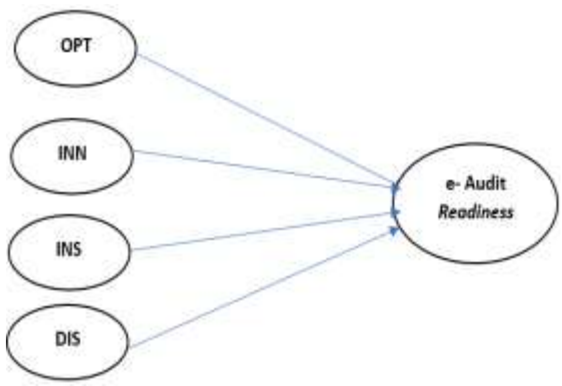

Figure 2. Conceptual Framework

H1: The OPT variable has a positive and significant relationship with e-Audit Readiness

H2: The INN variable has a positive and significant relationship with e-Audit Readiness
H3: The INS variable has a negative and significant relationship with e-Audit Readiness
H4: The DIS variable has a negative and significant relationship with e-Audit Readiness

MATERIALS & METHODS

The research design used was quantitative research, focusing on the careful measurement of a series of variables to answer questions by testing research hypotheses guided by theory (Creswell & Creswell, 2018). Quantitative research in this study utilized primary data sources, namely data obtained directly from research subjects for a specific purpose (Sekaran & Bougie, 2016).

In terms of time, this study was cross-sectional, meaning that data were collected at specific points in time to explain a phenomenon at that point (Creswell, 2012).

This research was conducted at all active banks in Medan City. The research period was from August 2024 to July 2025. The scale used in this study was the Likert scale (Likert, 1932), which measures individuals' attitudes by asking them to indicate how strongly they agree or disagree with a statement. It typically consists of a 5- or 7-point scale (McLeod, 2023).

The population in this study includes all active banks in Medan City. Based on data obtained from Google Maps (2025) using the Instant Data Scraper application, after data extraction, approximately 23 active banks were obtained. These 23 active banks encompass various types of banks operating in Medan City, including five state-owned enterprises (BUMN), three regionally owned enterprises (BUMD), 13 private banks, and two other banks. Therefore, this study employed a full sampling method due to the relatively small population size (Sekaran & Bougie, 2016).

The data collection required a questionnaire.

The online questionnaire used in this study was Google Forms. This study uses Smart-PLS software in the PLS SEM model analysis.

RESULT

Structural Equation Modeling Partial Least Squares (SEM PLS) Analysis

Figure 3 explains the PLS SEM framework used in this study.

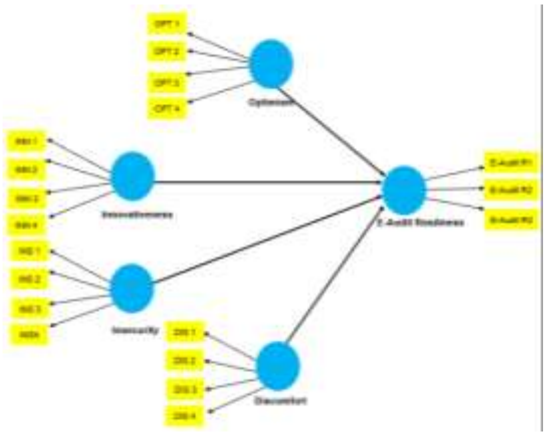

Figure 3. PLS SEM Statistical Model
Source: SmartPls, 2026

Outer Model Evaluation (Measurement Model) on Reflective Model Variables

1. **Convergent Validity Testing**

In testing convergent validity in the reflective model, an outer loading assessment is necessary. This assessment requires an outer loading value of >0.70 (Sarstedt et al., 2014). Next, convergent validity is also assessed using the AVE (Average Validity) assessment. The AVE assessment criterion is>0.50 or 50% (Sarstedt et al., 2014).

The outer loading results showed that the outer loadings for indicators INS 1 and DIS 1 were <0.7, or even <0.6, indicating that these indicators should be removed from the model. Indicators INN4 and INS3 were retained even though their outer loadings were <0.7. It is based on Hair and Alamer (2022), who stated that indicators with outer loadings <0.7 do not need to be removed if

the AVE of the variable they load in is >0.5. Furthermore, indicator INN4 is in the INN variable with an AVE value of 0.576 (>0.5), and INS 3 is in the INS variable with an AVE of 0.512 (>0.5).
Meanwhile, the other indicators have shown outer loading values >0.70, indicating that they adequately explain their variables. The following are the outer loading results before the removal of INS 1 and DIS 1.

Figure 4. Outer Loading results before removing INS 1 and DIS 1
Source: SmartPls, 2026

Next, the research model was created after removing INS 1 and DIS1. Figure 5 below presents the PLS SEM model after removing both indicators.

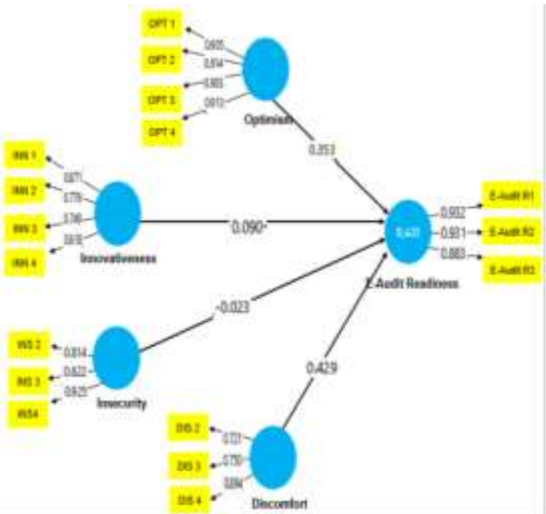

Figure 5. Model after the removal of INS 1 and DIS 1
Source: SmartPls, 2026

Next, the AVE values before and after the removal of INS 1 and DIS 1. The following tables 1 and 2 present this information.

Table 1. AVE Results Before Removal of INS 1 and DIS 1

Variable	AVE
Discomfort	0.506
E-Audit Readiness	0.838
Innovativeness	0.576
Insecurity	0.512
Optimism	0,826

Source: SmartPls, 2026

Table 2. AVE Results After Removal of INS 1 and DIS 1

Variable	AVE
Discomfort	0.627
E-Audit Readiness	0.838
Innovativeness	0.576
Insecurity	0.635
Optimism	0.826

Source: SmartPls, 2026

2. Variable Reliability Assessment

This assessment is indicated by CR values (rho_a and rho_c) > 0.70 (Henseler et al., 2009). Then, the second assessment is based on the Cronbach's alpha value, with a criterion of > 0.70 (Field, 2018). The CR values (rho a and rho c) have a value > 0.7 for all research variables. It indicates that all variables have good internal consistency. However, in the Cronbach alpha, the DIS variable had a Cronbach alpha of 0.682 (< 0.7), while the other four variables had Cronbach alpha values > 0.70 (above the criterion). In this case, removing one of the DIS indicators, namely DIS 1, also increased the Cronbach's alpha to 0.700 (the lower limit of the criterion).

Table 3. Cronbach's Alpha and Composite Reliability Results (CR rho_a and rho_c) Before Deleting INS 1 and DIS 1

Variable	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)
Discomfort	0.682	0.771	0.793
E-Audit Readiness	0.903	0.907	0.940
Innovativeness	0.790	1.040	0.843
Insecurity	0.704	0.919	0.799
Optimism	0.930	0.932	0.950

Source: SmartPls, 2026

Table 4. Cronbach's Alpha and Composite Reliability Results (CR rho_a and rho_c) After Deleting INS 1 and DIS 1

Variable	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)
Discomfort	0.700	0.744	0.833
E-Audit Readiness	0.903	0.908	0.940
Innovativeness	0.790	1.040	0.843
Insecurity	0.763	1.031	0.836
Optimism	0.930	0.932	0.950

Source: SmartPls, 2026

Discriminant Validity Assessment

To determine discriminant validity, three methods were used: cross-loading, the Fornell-Larcker criterion, and the HTMT ratio. In the cross-loading assessment, all indicators had higher outer loadings on their own variables than on other variables. It indicates that the indicators' ability to explain their own variables is much better than their ability to explain other variables.

Furthermore, in the Fornell-Larcker criterion, the square root of the AVE (average value) for all variables was greater than the correlation between the variables. The square root of the AVE for e-Audit Readiness (0.916) was higher than the DIS (0.533), INN (0.342), INS (0.404), and OPT (0.512). Similar findings were found for other variables. It indicates that all variables in the model share more variance with their constituent indicators than with other variables. Furthermore, the HTMT ratio findings indicate that all variables in this study scored less than 0.90 (90%). It means that all research variables have unique characteristics in explaining the dependent variable and do not overlap.

Table 5. Cross-Loading Results for OPT, INN, INS, DIS, and E-Audit Readiness

Indicator	Discomfort	E-Audit Readiness	Innovativeness	Insecurity	Optimism
DIS2	0.721	0.371	0.069	0.702	0.231
DIS3	0.750	0.357	0.155	0.381	0.146
DIS4	0.894	0.516	0.207	0.463	0.288
E-Audit R1	0.514	0.932	0.303	0.407	0.449
E-Audit R2	0.562	0.931	0.312	0.397	0.517
E-Audit R3	0.446	0.883	0.325	0.299	0.438
INN1	0.198	0.402	0.873	0.258	0.546
INN2	0.027	0.145	0.776	0.110	0.257
INN3	0.205	0.179	0.749	0.147	0.310
INN4	0.058	0.123	0.618	0.084	0.194
INS2	0.424	0.244	0.283	0.814	0.295
INS3	0.296	0.090	0.108	0.622	0.113
INS4	0.660	0.451	0.210	0.925	0.377
OPT1	0.245	0.439	0.505	0.353	0.905
OPT2	0.252	0.480	0.369	0.316	0.914
OPT3	0.281	0.439	0.506	0.384	0.903
OPT4	0.266	0.498	0.445	0.308	0.913

Source: SmartPls, 2026

Table 6. Fornell-Larcker Results for OPT, INN, INS, DIS, and E-Audit Readiness

Variable	Discomfort	E-Audit Readiness	Innovativeness	Insecurity	Optimism
Discomfort	0.792				
E-Audit Readiness	0.533	0.916			
Innovativeness	0.189	0.342	0.759		
Insecurity	0.637	0.404	0.229	0.797	
Optimism	0.287	0.512	0.500	0.376	0.909

Source: SmartPls, 2026

Table 7. HTMT Ratio Results for OPT, INN, INS, DIS, and E-Audit Readiness

Variable Correlation	Heterotrait-monotrait ratio (HTMT)
E-Audit Readiness <-> Discomfort	0.658
Innovativeness <-> Discomfort	0.232
Innovativeness <-> E-Audit Readiness	0.321
Insecurity <-> Discomfort	0.786
Insecurity <-> E-Audit Readiness	0.381
Insecurity <-> Innovativeness	0.243
Optimism <-> Discomfort	0.347
Optimism <-> E-Audit Readiness	0.556
Optimism <-> Innovativeness	0.490
Optimism <-> Insecurity	0.380

Source: SmartPls, 2026

Thus, the findings of the outer model have been presented, including convergent validity, variable reliability, and discriminant validity. All three assessments demonstrated values that met the established criteria. Therefore, the research model meets the requirements to proceed to the inner model assessment stage to answer the proposed hypotheses.

Evaluation of the Inner Model (Structural Model) on Reflective Model Variables

In this section, a bootstrapping process is conducted to test the hypothesis regarding the relationship between the independent variables (OPT, INN, INS, and DIS) and the dependent variable, e-Audit Readiness. The following are various findings from the inner model assessment.

1. Multicollinearity (VIF) Assessment

This assessment uses the VIF value as a reference. Based on the criteria of Hair and Alamer (2022), the VIF criterion is that VIF < 5.0 indicates no collinearity problem. However, a more conservative criterion is a VIF < 3.0. The following are the findings from this assessment.

Based on the findings, the VIF values for all variables in the original sample column are <3.0, indicating that none of the independent variables exhibit collinearity problems (Hair and Alamer, 2022). It means that the four independent variables, OPT, INN, INS, and DIS, do not interfere with each other in explaining the dependent variable, e-Audit Readiness.

Table 8. VIF Results of OPT, INN, INS, and DIS Variables on E-Audit Readiness

Variable Correlation	Original sample (O)	Sample mean (M)	2.5%	97.5%
Discomfort -> E-Audit Readiness	1.691	1.773	1.264	2.423
Innovativeness -> E-Audit Readiness	1.337	1.386	1.190	1.661
Insecurity -> E-Audit Readiness	1.806	1.902	1.347	2.609
Optimism -> E-Audit Readiness	1.477	1.513	1.279	1.804

Source: SmartPls, 2026

2. Path Coefficient Assessment

This assessment is conducted to test the research hypothesis using a bootstrapping approach. The criteria for answering the hypothesis are: if the P value is <0.05, the relationship between the variables is considered significant, and the hypothesis is accepted (Hair and Alamer, 2022). For the t-statistic, if (│t statistic│) > 1.65 (the critical value in the t-table for a one-sided test at a significance level of 0.05), the relationship between the variables is also considered significant (Cohen, 1988; Kline, 2023).

Based on the test results, it was found that:

a) The OPT variable showed a positive, highly significant relationship with e-Audit Readiness. These results indicate that the higher a person's confidence in e-Audit's ability to improve work quality, the higher their level of readiness for e-Audit. It likely occurs because banking personnel view e-Audit not simply as an additional feature, but as an instrument capable of improving the quality of their daily work. Given that banking auditors have busy schedules and high workloads, the perception that e-Audit can simplify task completion and help achieve targets is a significant factor driving their readiness to use e-Audit.

b) INN showed a positive but non-significant relationship with e-Audit Readiness. These findings indicate that personnel's confidence in their ability to be pioneers in the use of e-Audit does not significantly affect their readiness for the system. Differences in characteristics between individual banking personnel and related stakeholders likely cause this condition. Perceptions of INN are more individual, related to personnel's confidence in their own ability to adopt new technology. However, in the context of a banking organization, stakeholders have a more dominant role in determining strategic policies, including the implementation of e-Audit. Therefore, once an e-Audit adoption policy has been established, all personnel are still required to use the system, regardless of whether they feel capable of being pioneers.

c) INS reverse had a negative but non-significant relationship with e-Audit Readiness. These findings indicate that a decrease in readiness for e-Audit is accompanied by an increased sense of security regarding e-Audit, although the effect is very small. This result slightly contradicts the TRI theory, which states that a sense of security in using technology can increase user readiness. However, because the p-value is not statistically significant, this finding cannot be generalized to the broader population (Hair and Alamer, 2022). This phenomenon likely occurs because security is viewed as a "guarantee" provided by stakeholders to banking personnel using e-Audit. In other words, system security is a basic prerequisite for personnel to be willing to use e-Audit. However, this sense of security does not directly increase readiness for e-Audit use, as personnel perceive system security as a standard that the organization must guarantee.

d) DIS reverse had a very significant positive effect on e-Audit Readiness. It means that the more personnel believe e-Audit is easy an understand and use, the greater their readiness for it becomes. It is potentially because the ease-of-use aspect of a system is something personnel encounter daily. Therefore, even though e-Audit has become mandatory for banking stakeholders, its use remains at the general personnel level. When they perceive e-Audit as easy to understand and master, this can significantly improve their readiness to use it.

Table 9. Path Coefficient Results of OPT, INN, INS, and DIS Variables on E-Audit Readiness

Relationship	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Hypothesis
Discomfort -> E-Audit Readiness	0.429	0.412	0.105	4.092	0.000	**Accepted**
Innovativeness -> E-Audit Readiness	0.090	0.111	0.074	1.207	0.227	**Rejected**
Insecurity -> E-Audit Readiness	-0.023	0.001	0.101	0.226	0.821	**Rejected**
Optimism -> E-Audit Readiness	0.353	0.347	0.085	4.146	0.000	**Accepted**

Source: SmartPls, 2026

3. Adjusted R-Square Assessment

After processing with Smart-PLS, the adjusted R-Square value was 0.418 (41.8%). It means that the OPT, INN, INS, and DIS variables can explain 41.8% of e-Audit Readiness, with the remaining 58.2% explained by factors outside the model. According to Hair and Alamer (2022) criteria, this value is close to moderate (0.50). This finding indicates that the psychological variable TRI can explain e-Audit Readiness by almost half as much as the other factors.

It likely occurs because e-Audit Readiness is measured at the banking organizational level, which is more influenced by the policies of relevant stakeholders. When stakeholders establish e-Audit implementation policies, all banking personnel must comply with them. Therefore, factors outside the model, such as banking stakeholder policies, are potentially more effective in explaining e-Audit Readiness than the psychological factors in the TRI.

Table 10. Adjusted R-Square Results of OPT, INN, INS, and DIS Variables on E-Audit Readiness

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
E-Audit Readiness	0.418	0.450	0.063	6.647	0.0

Source: SmartPls, 2026

4. F-Square Assessment

Based on the findings, the F-value for the OPT variable was 0.148 (close to the medium range). It indicates that OPT has a significant effect on the R-square of e-Audit Readiness. Furthermore, the INN variable yielded an F-square value of 0.011 (<0.02), indicating a small effect on the R-square of e-Audit Readiness. The INS variable yielded an F-square value of 0.001 (far < 0.02), indicating that INS has a very small effect on the R-square of e-Audit Readiness. Finally, the DIS variable obtained an F-square value of 0.192 (>0.15). It indicates that DIS has a significant effect and is a major determinant in the R-square of e-Audit Readiness.

The factors contributing to these findings are thought to stem from the fact that the OPT and DIS reverse variables are directly related to the technical aspects of daily technology use. OPT reflects the perception of increased productivity through e-Audit, while DIS indicates the perceived ease of use of e-Audit. Both of these aspects are directly related to personnel work productivity and, therefore, effectively increase user e-Audit Readiness.

Conversely, the INN and INS reverse variables are more related to non-technical aspects. INN reflects an individual's subjective perception of their ability to quickly master e-Audit, while INS reflects the perceived security of the system, which the organization essentially guarantees. Because they do not directly affect personnel and auditors' daily productivity, these two variables are less effective in driving user e-Audit Readiness.

Table 11. F-Square results of OPT, INN, INS, DIS variables on E-Audit Readiness

Variable	Original sample (F *Square*)	Kriteria(Cohen (1988)
Discomfort -> E-Audit Readiness	0.192	Intermediate
Innovativeness -> E-Audit Readiness	0.011	Small
Insecurity -> E-Audit Readiness	0.001	Very small
Optimism -> E-Audit Readiness	0.148	Pre-intermediate

Source: SmartPls, 2026

5. Q Square Assessment

The following explains the Q-square value used to assess the model's predictive relevance. Based on the PLS Predict procedure, the Q Square Predict value was found to be 0.365 (Q square predict > 0). Based on the criteria of Shmueli et al. (2019) and Hair and Alamer (2022), this value indicates the model has good predictive relevance. It means that the variables in the model have a good ability to predict e-Audit Readiness in the future or with subjects outside the studied sample.

Table 12. Q Square Results of OPT, INN, INS, DIS variables on E-Audit Readiness

Variable	Q^2predict	RMSE	MAE
E-Audit Readiness	0.365	0.810	0.584

Source: SmartPls, 2026

CONCLUSION

Furthermore, based on the inner model analysis, OPT and DIS were found to be significant on e-Audit Readiness. In addition, INN and INS had no significant effect on e-Audit Readiness. Of the two significant variables, DIS made a greater contribution, with a path coefficient of 0.429, which outperformed OPT by 0.353 and had the same P value (0.000). This finding confirms that perceptions of the difficulty of using e-Audit and its complex guidelines (DIS) are the main determinants of user readiness to use the system. This factor exceeds the perception of e-Audit effectiveness (OPT), even though this is also a major determinant of e-Audit Readiness.

LIMITATIONS

This research is far from perfect and requires further investigation of the topic under discussion. Based on the research conducted, several limitations were encountered in the field, including:

1. The sample size of banks willing to participate was not entirely optimal. Eleven of the 23 banks willing to participate included all state-owned banks, one of the largest regionally-owned banks, and five large national private banks operating in Medan. Although this composition reflects the city's major banking institutions, the level of participation was not entirely optimal. This difficulty is likely due to banks' tendency to be more cautious in their regulations, which include considerations of participation in research. Furthermore, the lack of support from relevant authorities in the necessary data collection process may also limit the scope of bank participation. This implication limits the generalizability of the research results to the context of banking organizations in Medan.
2. The questionnaire served as the sole tool in the data collection process. In this study, respondents were only asked to provide their assessment of the research object. However, this was done without further interviews. Therefore, the assessment results more closely reflect a quantitative measurement of respondents' perceptions of e-Audit readiness. However, this study was unable to explore in depth other factors that could influence user readiness for e-Audit.
3. Potential respondent perception bias. This study also faced the potential for bias in responses from some respondents. During the research, general concepts about e-Audit were included in the questionnaire. However, in practice, not all personnel shared the same understanding of the

system. This difference in understanding can also lead to misperceptions, thereby reducing the accuracy of the variables studied. Furthermore, using a single questionnaire can introduce common method bias, which is a frequent issue in data collection.

4. Limited access across divisions in private banks. This study encountered limited access for personnel across divisions in private banks. It resulted in an unequal distribution of respondents compared to state-owned and regional-owned banks. This imbalance in respondents may lead to differences in perceptions of the main variables measured in this study. However, the analysis of the total average score indicates that the e-Audit Readiness level of private banks is relatively close to that of state-owned and regional-owned banks. Nevertheless, interpreting the e-Audit Readiness level between private banks and state-owned and regional-owned banks requires careful consideration. Cross-divisional limitations in private banks mean that respondents are concentrated solely in customer service divisions, which are not fully involved in core e-Audit operations. Therefore, although e-Audit readiness scores are relatively comparable, these findings do not fully reflect perceptions of e-Audit readiness in private banks.

Declaration by Authors

Acknowledgement: None

Source of Funding: None

Conflict of Interest: No conflicts of interest declared.

REFERENCES

1. Adepoju. (2022). Transforming internal audit and control through digital innovation. KPMG in Nigeria. https://assets.kpmg.com/content/dam/kpmg/ng/pdf/transforming-ia-and-ic-through-digital-innovation-new-latest.pdf
2. Agarwal, R., & Prasad, J. (1998). A conceptual and operational definition of personal innovativeness in the domain of information technology. Information Systems Research, 9(2), 204–215. https://doi.org/10.1287/isre.9.2.204
3. Alhammadi, K., Marashdeh, H., & Hussain, M. (2023). Assessing the effect of innovation diffusion and technology readiness theories on attitude, behavioral intention, and implementation of smart learning. Cross-Cultural & Strategic Management, 30(4), 657-675. https://doi.org/10.1108/CCSM-12-2022-0213
4. Almaqtari, F. A., Farhan, N. H. S., Al-Hattami, H. M., Elsheikh, T., & Al-dalaien, B. O. A. (2024). The impact of artificial intelligence on information audit usage: Evidence from developing countries. Journal of Open Innovation: Technology, Market, and Complexity, 10(2), 100298. https://doi.org/10.1016/j.joitmc.2024.100298
5. Alqudah, H., Mansour, A. Z., Rawashdeh, B. S., Lutfi, A., Al Barrak, T., Almaiah, M. A., & Alrawad, M. (2024). Enhancing the internal auditors' effectiveness in Jordanian companies: The impact of cloud-based accounting usage and the moderating role of digital proficiency. Computers in Human Behavior Reports, 15, 100442. https://doi.org/10.1016/j.chbr.2024.100442
6. Bai, G. H. (2017). Research on the application and influence of auditing artificial intelligence, in DEStech Transactions on Social Science, Education and Human Science (pp. 245-249). https://www.researchgate.net/publication/326798038_Research_on_the_Application_and_Influence_of_Auditing_Artificial_Intelligence
7. Beach, T., Yeung, J., Nisbet, N., & Rezgui, Y. (2024). Digital approaches to construction compliance checking: Validating the suitability of an ecosystem approach to compliance checking. Advanced Engineering Informatics, 59, 102288. https://doi.org/10.1016/j.aei.2023.102288
8. Begkos, C., Antonopoulou, K., & Ronzani, M. (2024). To datafication and beyond: Digital transformation and accounting technologies in the healthcare sector. The British Accounting Review, 56(4), 101259. https://doi.org/10.1016/j.bar.2023.101259
9. Castka, P., Searcy, C., & Mohr, J. (2020).

Technology-enhanced auditing: Improving veracity and timeliness in social and environmental audits of supply chains. Journal of Cleaner Production, 258, 120773. https://doi.org/10.1016/j.jclepro.2020.120773
10. Chen, W., Liu, S., Smieliauskas, W. J., & Trippen, G. (2012). Influence factors analysis of online auditing performance assessment: A combined use between AHP and GIA. Kybernetes, 41(5/6), 587-598. https://doi.org/10.1108/03684921211243257
11. Cimbaljevic, M., Bajrami, D., Kovačić, S., Pavluković, V., Stankov, U., & Vujičić, M. (2023). Employees' technology adoption in the context of smart tourism development: The role of technological acceptance and technological readiness. European Journal of Innovation Management. https://doi.org/10.1108/EJIM-09-2022-0516
12. Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Lawrence Erlbaum Associates.
13. Creswell, J. W. (2012). Educational research: Planning, conducting, and evaluating quantitative and qualitative research (4th ed.). Pearson Education.
14. Creswell, J. W., & Creswell, J. D. (2018). Research design: Qualitative, quantitative, and mixed methods approaches (5th ed.). SAGE Publications.
15. Dai, J., & Vasarhelyi, M. A. (2016). Imagineering Audit 4.0. Journal of Emerging Technologies in Accounting, 13(1), 1–15. https://doi.org/10.2308/jeta-10494
16. Deloitte. (2023). Using blockchain to drive supply chain transparency: Use cases and future outlook on blockchain in supply chain management. https://www2.deloitte.com/content/dam/Deloitte/us/Documents/us-ent-supply-chain-pov.pdf
17. Dharma, D. P. B., Sandhyaduhita, P. I., Pinem, A. A., & Hidayanto, A. N. (2017). Antecedents of intention-to-use of e-Audit system: A case of the Audit Board of the Republic of Indonesia. International Journal of Business Information Systems, 26(2), 185-204.
18. Elvis, T. E., & Kim, H. K. (2022). Unified perspective of technology readiness index (TRI) and technology acceptance model (TAM) for adoption of digital pills. Journal of System and Management Sciences, 12(4), 101-114. https://doi.org/10.33168/JSMS.2022.0407
19. Erişen, O., & Erer, M. (2023). Exploring the impacts of digitalization on the internal audit profession. Journal of Research in Business, 8(1), 171-190. https://dergipark.org.tr/en/download/article-file/2682173
20. Ernst & Young. (2020). Realize blockchain's value proposition: Scaling business ecosystems.
21. Etim, E., & Daramola, O. (2023). Investigating the E-Readiness of Informal Sector Operators to Utilize Web Technology Portal. Sustainability, 15(4), 3449. https://doi.org/10.3390/su15043449
22. Field, A. (2018). Discovering statistics using IBM SPSS Statistics (5th ed.). SAGE Publications Ltd.
23. Flavian, C., Perez-Rueda, A., Belanche, D., & Casaló, L. V. (2021). Intention to use analytical artificial intelligence (AI) in services–The effect of technology readiness and awareness. Journal of Service Management, 33(2), 293-320. https://doi.org/10.1108/JOSM-10-2020-0378
24. Florestiyanto, M. Y. (2015). Evaluasi kesiapan pengguna dalam adopsi sistem informasi terintegrasi di bidang keuangan menggunakan metode technology readiness index. Seminar Nasional Informatika (SEMNASIF), 1(4). https://media.neliti.com/media/publications/175140-ID-evaluasi-kesiapan-pengguna-dalam-adopsi.pdf
25. Fortune (2024, January 12). The CEO and AI: What's ahead in 2024. https://fortune.com/2024/01/12/ai-playbook-c-suite-ceo/
26. Gambetta, N., García-Benau, M. A., & Zorio-Grima, A. (2016). Data analytics in banks' audit: The case of loan loss provisions in Uruguay. Journal of Business Research, 69(11), 4793-4797.
27. Google Maps. (2025). Daftar perbankan di Kota Medan.
28. Gu, Y., Dai, J., & Vasarhelyi, M. A. (2023). Audit 4.0-based ESG assurance: An example of using satellite images on GHG emissions. International Journal of Accounting Information Systems, 50, 100625. https://doi.org/10.1016/j.accinf.2023.100625
29. Hair, J., & Alamer, A. (2022). Partial Least

Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. Research Methods in Applied Linguistics, 1(3), 100027. https://doi.org/10.1016/j.rmal.2022.100027
30. Hamza, M., Alkabbji, R., Almbydeen, T. H., Almubaydeen, A., & Bajunaid, K. (2023). The impact of applying electronic internal auditing in raising the efficiency of financial performance in Jordanian commercial banks. In Artificial Intelligence (AI) and Finance (pp. 521-532). Cham: Springer Nature Switzerland
31. Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. In New challenges to international marketing (Vol. 20, pp. 277-319). Emerald Group Publishing Limited.
32. Huy, L. V., Nguyen, P. T. H., Pham, L., & Berry, R. (2019). Technology readiness and satisfaction in Vietnam's luxury hotels. International Journal of Management and Decision Making, 18(2), 183-208. https://doi.org/10.1504/IJMDM.2019.098648
33. Kamdjoug, J. R. K., Sando, H. D., Kala, J. R., Teutio, A. O. N., Tiwari, S., & Wamba, S. F. (2024). Data analytics-based auditing: a case study of fraud detection in the banking context. Annals of Operations Research, 340(2), 1161-1188. http://doi.org/10.1007/s10479-024-06129-8
34. Katadata. (2023, September 20). Indeks Kesiapan Digital Asia Tenggara, Skor Indonesia Tergolong Rendah. Databoks. https://databoks.katadata.co.id/datapublish/2023/09/20/indeks-kesiapan-digital-asia-tenggara-skor-indonesia-tergolong-rendah
35. Kaushik, M. K., & Agrawal, D. (2021). Influence of technology readiness in adoption of e-learning. International Journal of Educational Management, 35(2), 483-495. https://doi.org/10.1108/IJEM-04-2020-0216
36. Kementerian Lingkungan Hidup dan Kehutanan. (2020). Itjen KLHK Kembangkan e-Audit.
37. Kline, R. B. (2023). Principles and practice of structural equation modeling (5th ed.). Guilford Press.
38. KPMG. (2023). Blockchain and generative AI: A perfect pairing?. https://kpmg.com/kpmg-us/content/dam/kpmg/pdf/2023/blockchain-generative-ai.pdf
39. Likert, R. (1932). A technique for the measurement of attitudes. Archives of Psychology, 22(140), 55.
40. Liljander, V., Gillberg, F., Gummerus, J., & Van Riel, A. (2006). Technology readiness and the evaluation and adoption of self-service technologies. Journal of Retailing and Consumer Services, 13(3), 177-191. https://doi.org/10.1016/j.jretconser.2005.08.004
41. Lin, C. H., Shih, H. Y., & Sher, P. J. (2007). Integrating technology readiness into technology acceptance: The TRAM model. Psychology & Marketing, 24(7), 641–657. https://doi.org/10.1002/mar.20177
42. LKPP. (2024). Siaran Pers LKPP Luncurkan Fitur Pengawasan e-Audit Cegah Praktik Curang pada Katalog Elektronik. https://www.lkpp.go.id/read/bu/siaran-pers-lkpp-luncurkan-fitur-pengawasan-e-Audit-cegah-praktik-curang-pada-katalog-elektronik
43. McLeod, S. A. (2023). Likert scale questionnaire: Examples & analysis. SimplyPsychology Profesional. https://www.simplypsychology.org/likert-scale.html
44. Munoko, I., Brown-Liburd, H. L., & Vasarhelyi, M. (2020). The ethical implications of using artificial intelligence in auditing. Journal of Business Ethics, 167(2), 209-234. https://doi.org/10.1007/s10551-019-04407-1
45. Nguyen, P. T., Kend, M., & Le, D. Q. (2024). Digital transformation in Vietnam: The impacts on external auditors and their practices. Pacific Accounting Review, 36(1), 144-160. https://doi.org/10.1108/PAR-04-2023-0051
46. Oh, J. C., Yoon, S. J., & Chung, N. (2014). The role of technology readiness in consumers' adoption of mobile internet services between South Korea and China. International Journal of Mobile Communications, 12(3), 229–248. https://doi.org/10.1504/ijmc.2014.061460
47. O'Hern, S., & Louis, R. S. (2023). Technology readiness and intentions to use conditionally automated vehicles. Transportation Research Part F: Traffic Psychology and Behaviour, 94, 1-8. https://doi.org/10.1016/j.trf.2023.02.001
48. OJK. (2023). OJK Dorong Auditor Internal Terapkan Teknologi dalam GRC

Terintegrasi. https://ojk.go.id/id/berita-dan-kegiatan/info-terkini/Pages/OJK-Dorong-Auditor-Internal-Terapkan-Teknologi-dalam-GRC-Terintegrasi-.aspx

49. Ozel, B., Nasir, V. A., & Turker, H. B. (2023). Determinants of smart home adoption and differences across technology readiness segments. Technological Forecasting and Social Change, 197, 122924. https://doi.org/10.1016/j.techfore.2023.122924
50. Parasuraman, A. (2000). Technology Readiness Index (TRI): A multiple-item scale to measure readiness to embrace new technologies. Journal of Service Research, 2(4), 307-320.
51. Parasuraman, A., & Colby, C. L. (2015). An updated and streamlined technology readiness index: TRI 2.0. Journal of Service Research, 18(1), 59-74.
52. PricewaterhouseCoopers. (PwC) (2024). Redefining the audit: The impact of digitalisation in finance and accounting. https://www.pwc.ch/en/insights/accounting/redefining-the-audit.html
53. PricewaterhouseCoopers. (PwC). (2023). Transformasi menjadi Next Gen audit internal - mengedepankan aspek digitalisasi, ketangkasan, dan peningkatan keterampilan. PWC Indonesia. https://www.pwc.com/id/en/media-centre/press-release/2023/indonesian/transformasi-menjadi-next-gen-audit-internal-mengedepankan-aspek-digitalisasi-ketangkasan-dan-peningkatan-keterampilan.html
54. Qasem, Z. (2021). The effect of positive TRI traits on centennials adoption of try-on technology in the context of E-fashion retailing. International Journal of Information Management, 56, 102254. https://doi.org/10.1016/j.ijinfomgt.2020.102254
55. Rahman, M. J., Zhu, H., & Yue, L. (2024). Does the adoption of artificial intelligence by audit firms and their clients affect audit quality and efficiency? Evidence from China. Managerial Auditing Journal. https://doi.org/10.1108/MAJ-03-2023-3846
56. Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. European Business Review, 26(2), 106-121. https://doi.org/10.1108/EBR-10-2013-0128
57. Sekaran, U., & Bougie, R. (2016). Research methods for business: A skill-building approach (7th ed.). Wiley.
58. Shariffuddin, N. S. M., Azinuddin, M., Yahya, N. E., & Hanafiah, M. H. (2023). Navigating the tourism digital landscape: The interrelationship of online travel sites' affordances, technology readiness, online purchase intentions, trust, and E-loyalty. Heliyon, 9(8), e19135. https://doi.org/10.1016/j.heliyon.2023.e19135
59. Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. European Journal of Marketing, 53(11), 2322–2347. https://doi.org/10.1108/EJM-02-2019-0189
60. Tu, Y., Liu, W., & Yang, Z. (2023). Exploring the influence of service employees' characteristics on their willingness to work with service robots. Journal of Service Management, 34(5), 1038-1063. https://doi.org/10.1108/JOSM-05-2022-0174
61. Yosser, I. M., Idrus, S. Z. B. S., & Ali, A. A. E. (2020, April). Technology readiness index 2.0 as predictors of e-health readiness among potential users: A case of conflict regions in Libya. In Journal of Physics: Conference Series, 1529(3), 032009. IOP Publishing. https://doi.org/10.1088/1742-6596/1529/3/032009
62. Zolila. (2024). E-audit menjaga integritas, objektivitas dan transparansi. Badan Pemeriksa Keuangan Republik Indonesia Perwakilan Sumatera Barat. https://sumbar.bpk.go.id/e-audit-menjaga-integritas-objektivitas-dan-transparansi/

How to cite this article: Hendra Mulnandar, Sambas Ade Kesuma, Rina Br. Bukit. Measuring e-audit readiness in the banking sector in Medan city: perspective of technology readiness index 2.0. *International Journal of Research and Review*. 2026; 13(6): 283-297. DOI: *https://doi.org/10.52403/ijrr.20260629*

******