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EXPLORING THE FACTORS THAT INFLUENCE INDONESIAN AUDITORS' INTENTION TO USE BIG DATA ANALYTICS: APPLICATION OF THE UTAUT MODEL WITH PERCEIVED RISK AND TRUST

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ABSTRACT

The adoption of Big Data Analytics (BDA) in auditing is vital in the fourth industrial revolution era, yet imany auditors in Indonesia hesitate to embrace these tools. This study aims to identify factors influencing Indonesian auditors' intention to use BDA, applying the Unified Theory of Acceptance and Use of Technology (UTAUT) model and including perceived risk and trust variables. Using quantitative approach, questionnaires were distributed via Google Form to 134 auditor respondents in Indonesia, primarily in DKI Jakarta. Data were analyzed using Structural Equation Modeling (SEM) with SmartPLS. Result shows that performance expectancy, effort expectancy, social influence, and trust significantly influence auditors' intention to use BDA, while perceived risk does not significantly affect the intention to use BDA. This study underscores the importance of strengthening auditor trust in technology to enhance BDA adoption, with training and technical support identified as supportive factors to increase auditor comfort and confidence in using BDA in the future, also future research could explore the longitudinal impacts of BDA adoption or extend the study to diverse industries and regions.

Keywords: Big Data Analytics (BDA), Auditor, UTAUT, Perceived Risk, Trust

INTRODUCTION

The Fourth Industrial Revolution, marked by technological advancements like IoT, Big Data, Cloud, and Blockchain, has significantly transformed business operations (Haseeb et al., 2019). These technologies enhance performance and efficiency, helping companies stay competitive. However, modern systems generate vast amounts of data, impacting financial reporting and necessitating additional verification (Yoon et al., 2015).

Big Data, characterized by its volume, variety, and velocity, involves complex data sets that require sophisticated processing techniques (Gartner, 2016). This includes both structured and unstructured data, such as text and multimedia. Advanced analytical tools are essential for managing and analyzing this data to provide accurate insights for decision-making (Cao et al., 2015; Salijeni et al., 2019). With over 98% of global information stored electronically, traditional analysis methods are inadequate, and Data Analytics offers improved handling of complex data (Rezaee & Wang, 2019).

In auditing, Big Data Analytics enhances business performance and financial reporting by processing extensive datasets to uncover valuable insights (Haseeb et al., 2019). It improves the effectiveness and reliability of audit results, especially for large companies with substantial data volumes. The primary aim of an external audit is to assess whether financial statements accurately reflect a client's financial position according to accepted accounting principles (Yoon et al., 2015). Big Data Analytics facilitates automatically detecting anomalies, errors, and patterns over time, significantly benefiting external auditors (Appelbaum et al., 2017). It is useful during substantive testing, audit reporting, and risk assessment phases, including client acceptance and fraud detection

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(Cao et al., 2015). Offering deeper insights into clients' business environments reduces the risk of incorrect conclusions and substantially enhances audit quality (Dagilienė & Klovienė, 2019).

Despite its potential, Big Data Analytics is underutilized in auditing. Research indicates that auditors in public accounting firms have not fully adopted this technology, often lacking knowledge of its effective application in audits (Dagiliene & Kloviene, 2019). In Indonesia, the use of Big Data Analytics remains low, primarily confined to sectors like telecommunications, banking, and consumer goods (Sirait, 2016). Auditors must adapt to the increasing use of Big Data and Data Analytics in client operations, which introduces new challenges. They must utilize advanced predictive and prescriptive analytical tools for complex audit tasks, highlighting the importance of adopting technology to ensure relevance and accuracy in modern audits (Appelbaum et al., 2017).

To explore the factors influencing technology adoption by auditors, the UTAUT model was selected due to its prominence in evaluating technology adoption within organizational settings. Unlike UTAUT2 (Venkatesh et al., 2012), which focuses on consumer markets by incorporating habit, hedonic motivation, and price value, UTAUT is tailored for organizational environments. Similarly, UTAUT3 (Farooq et al., 2017) builds on UTAUT2 by adding personal innovativeness in IT but is intended for consumer contexts and academic settings. UTAUT identifies four key factors: performance expectancy, effort expectancy, social Influence, and facilitating conditions (Venkatesh, 2003).

Performance Expectancy is the belief that using a technological system will enhance productivity (Venkatesh et al., 2003). Research shows this factor is crucial for technology adoption across various contexts, including auditing. Auditors are more likely to adopt technologies like CAATs and Blockchain if they believe these tools will improve their performance (Esawe, 2022; Penney et al., 2021; Pedrosa et al., 2020; Al-Hiyari et al., 2019).

Effort Expectancy pertains to the ease of use of new technology. Simpler technologies are more likely to be adopted (Venkatesh et al., 2003). Studies indicate that when auditors perceive technology as easy to use, they are more likely to adopt it. This perception enhances their expected performance from using the technology (Yosephine et al., 2019; Kim et al., 2016; Penney et al., 2021).

Facilitating Conditions involve the availability of resources and support necessary for technology use. Auditors are more inclined to use new technologies when supported by resources like user guides and training (Venkatesh et al., 2003). Effective facilitation has positively impacted technology adoption, including Big Data Analytics (Alalwan et al., 2017; Cabrera-Sábrera and Villarejo-Ramos, 2019; Yosephine et al., 2019).

Social Influence reflects how opinions and actions of peers affect technology adoption. Social Influence can significantly impact auditors' willingness to adopt new technologies like Blockchain in auditing. If peers or clients support using technology, auditors are more likely to follow suit (Ferri et al., 2020; Curtis and Payne, 2014).

Trust is crucial for technology acceptance, particularly with sensitive data in Big Data Analytics. Trust in technology providers affects the decision to use and continue new technologies. High trust reduces perceived risk and effort required for technology adoption, influencing performance and effort expectancy (Alalwan et al., 2017; Almagrashi et al., 2023; Penney et al., 2021; Alkali & Mansor, 2017).

Perceived risks in implementing Big Data Analytics include limited resources and skilled personnel, which affect adoption, particularly in small audit firms. Data security risks and perceived risks, such as cyber-attacks and data loss, further complicate adoption (Wang et al., 2016; Horak & Boksova, 2017; Dagilienė & Klovienė, 2019). Building trust can mitigate these risks and encourage technology adoption by addressing security concerns (Featherman & Pavlou, 2003; Penney et al., 2021; Wang & Lin, 2016).

Big Data Analytics (BDA) represents a revolutionary tool that can improve audit quality, efficiency, and reliability. However, adopting BDA remains limited in Indonesia, presenting challenges for auditors who must navigate the increasingly data-driven business environment. This study explores factors influencing auditors' intention to implement Big Data Analytics, to enhance audit quality and support more efficient decision-making for financial report users. Additionally, it examines how auditors adopt Big Data Analytics using the Unified Theory of Acceptance and Use of Technology (UTAUT) model, incorporating perceived risk and trust. The model seeks to identify factors affecting auditors' attitudes toward new technology, bridging the gap between auditors and technological advancements essential to bridge this gap by exploring the factors that influence Indonesian auditors' intention to use BDA. By identifying these factors, this research provides valuable insights into fostering technological adoption and advancing audit practices in Indonesia.

BIG DATA ANALYTICS

Big Data Analytics (BDA) denotes the use of sophisticated computational instruments to examine extensive quantities of organized and unstructured data, providing significant insights for informed decision-making. Characterized by volume, diversity, velocity, and veracity, Big Data Analytics (BDA) enables enterprises to evaluate intricate datasets and derive meaningful insights (Gartner, 2016). In auditing, Big Data Analytics (BDA) improves the efficiency and precision of audit operations by automating activities such as anomaly detection, fraud identification, and trend analysis, hence enhancing audit quality (Appelbaum et al., 2017; Yoon et al., 2015). Notwithstanding its advantages, obstacles like data security vulnerabilities, the need for proficient staff, and reluctance towards technology adoption impede extensive deployment (Dagilienė & Klovienė, 2019). By tackling these challenges via training, supporting frameworks, and stringent security protocols, BDA can revolutionize auditing procedures and align them with the requirements of the digital era.

UNIFIED THEORY OF ACCEPTANCE AND USE OF TECHNOLOGY (UTAUT) MODEL

The Unified Theory of Acceptance and Use of Technology (UTAUT) model, introduced by Venkatesh et al. (2003), offers a thorough framework for comprehending technology adoption within organizational contexts. It delineates four principal components that affect behavioral intention and use behavior: performance expectation, effort expectancy, social influence, and enabling factors. These characteristics jointly explain why humans embrace or oppose new technology. Extensions such as UTAUT2 and UTAUT3 have included further factors, including trust, perceived risk, and hedonic incentive, to enhance the understanding of technology acceptance across many settings (Farooq et al., 2017; Almagrashi et al., 2023). The UTAUT model has been extensively used to examine the uptake of technologies such as mobile banking, e-learning, and Big Data Analytics, demonstrating its adaptability in elucidating user behavior. The approach is crucial in assessing auditors' readiness to incorporate new techniques like as BDA into their processes, providing valuable information to policymakers and organizations on addressing adoption challenges.

METHODS

This research focuses on auditors employed by companies and uses quantitative techniques, specifically surveys. Data was collected via Google Forms, with questions adapted from existing research. Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions were adapted based on (Venkatesh et al., 2003 Ferri et al., 2020 Penney et al., 2021), and (Esawe et al., 2022) in relation to the UTAUT model. Perceived Risk was assessed using adaptations from (Featherman & Pavlou, 2003; Xie et al., 2021), and (Penney et al., 2021). Trust was evaluated through adaptations from (Gefen et al., 2003; Alalwan et al., 2017; Penney et al., 2021).

The research targeted auditors working for Public Audit Firms in the Jakarta area. The sample size was determined using the 10:1 ratio from (Hair et al., 2017), which necessitates ten samples per variable indicator. With seven indicators, the minimum sample size required was calculated to be 70, derived from the equation $S=I\times10$ (where S is the sample size and I is the number of indicators).

Data analysis employed Structural Equation Modelling – Partial Least Squares (SEM–PLS) using SmartPLS version 4. This method involves two main evaluation stages: the Measurement Model (Outer Model) and the Structural Model (Inner Model). For the Measurement Model, validity and reliability are assessed. Convergent Validity is confirmed if the Average Variance Extracted (AVE) exceeds 0.50 and the outer loading is above 0.70. Discriminant Validity is evaluated by ensuring that each indicator's loading is higher for its intended variable compared to others and that the square root of AVE surpasses the correlation values. Reliability is checked using composite reliability and Cronbach's alpha, with acceptable thresholds being above 0.70 and 0.60, respectively.

In evaluating the Structural Model (Inner Model), relationships between variables are analyzed. The coefficient of determination (R^2) shows how well independent variables explain the variance in the dependent variable, with higher values indicating better explanatory power. Path coefficients range from -1 to +1, reflecting the strength and direction of relationships. T-Statistics, calculated through bootstrapping in SmartPLS, determine significance: values above 1.96 indicate significant relationships, while those below suggests insignificance (Ghozali, 2016).

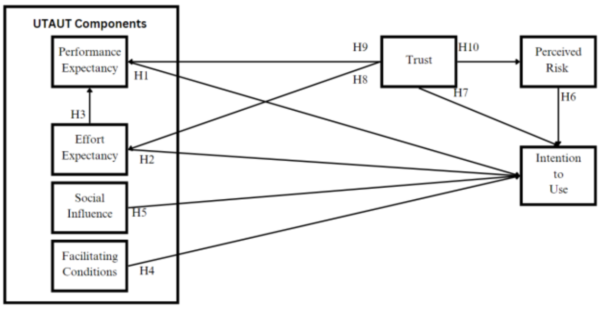

Figure 1 : Research Model

Table 1 Variable Operationalization

Variable	Indicator	Code	Statement	Source
Performance Expectancy (X1)	*perceived usefulness*	X1_1	The use of Big Data Analytics is beneficial in fulfilling my responsibilities in auditing.	(Venkatesh et al., 2003; Ferri et al., 2020)
	perception of increased task efficiency	X1_2	I can complete tasks faster when using Big Data Analytics.	
	perception of increased productivity	X1_3	The use of Big Data Analytics makes the audit process more productive.	
	outcome expection	X1_4	Using Big Data Analytics will allow me to improve audit quality.	
Effort Expectancy (X2)	*interaction*	X2_1	The use of Big Data Analytics for audit activities is not stressful.	(Venkatesh et al., 2003; Ferri et al., 2020)
	skillfulness	X2_2	Becoming proficient in using Big Data Analytics is easy for me.	
	ease of use	X2_3	It will be easy for me to use Big Data Analytics.	
	degree of ease to learn	X2_4	I can quickly learn how to use Big Data Analytics.	
Social Influence (X3)	*senior management*	X3_1	My supervisor believes I should learn how to use Big Data Analytics for audit activities.	(Venkatesh et al., 2003; Ferri et al., 2020)
	influential people	X3_2	People around me think I should use Big Data Analytics.	
	important people	X3_3	The people who are important to me believe I need to use Big Data Analytics.	
	peer opinion	X3_4	The people I work with believe I should use Big Data Analytics in audit activities.	
Facilitating Conditions (X4)	*availability of resources*	X4_1	My company has the necessary resources to use Big Data Analytics.	(Venkatesh et al., 2003; Penney et al., 2021)

	availability of knowledge	X4_2	I have the knowledge required to use Big Data Analytics.	
	system compatibility	X4_3	Big Data Analytics is compatible with other technologies I use (e.g., Big Data Analytics can be accessed via a computer).	
	availability of support	X4_4	My company provides adequate support to address issues encountered while using Big Data Analytics.	
Trust (X5)	*ability*	X5_1	I trust Big Data Analytics services.	(Gefen et al., 2003; Alawan, 2017; Penney et al., 2021)
	benevolence	X5_2	I am confident that Big Data Analytics services are reliable.	
	integrity	X5_3	I believe that the Big Data Analytics service provider is trustworthy and maintains user privacy.	
	technology reliability	X5_4	I trust that Big Data Analytics has the ability to perform its tasks.	
Perceived Risk (X6)	*privacy*	X6_1	I would not feel secure when sending sensitive information using Big Data Analytics.	(Featherman dan Pavlou, 2003; xie et al., 2021; Penney et al., 2021)
	performance	X6_2	Using Big Data Analytics will involve more technical risks compared to traditional audit methods.	
	financial	X6_3	Using Big Data Analytics will involve more financial risks compared to traditional audit methods.	
	overall risk	X6_4	How do you assess the overall risk of using Big Data Analytics for conducting audits?	
Intention to Use (Y)	*usage intention*	Y_1	I intend to use Big Data Analytics in the audit process regularly.	(Venkatesh et al., 2003; Penney et al., 2021; Esawe, 2022)
	prediction of use of system	Y_2	I expect to use Big Data Analytics in the future.	
	plan to use	Y_3	I plan to use Big Data Analytics soon (in the near future).	
	peer advocacy	Y_4	I would recommend Big Data Analytics to my colleagues.	

Source: Author

ANALYSIS

DESCRIPTIVE ANALYSIS

The questionnaire was completed by a diverse group of 134 respondents. Notably, 44.78% were female and 55.22% were male. Regarding the type of KAP, 56.72% worked in Big 4 Public Firms while 43.28% were part of non-big 4 public firms. All respondents were from DKI Jakarta, with no representation from other regions. Age distribution showed that 70.15% were under 25 years old, 20.90% were between 25-30 years, 1.49% were between 30-35 years, 6.72% were between 35-40 years, and 0.75% were over 40 years. Regarding work positions, 38.06% were Junior Auditors, 26.12% were Senior Auditors, 28.36% were Associates, 5.22% were Interns, 1.49% were Managers, and 0.75% were Partners. Their work experience varied, with 73.13% having 1-5 years, 18.66% having 6-10 years, 7.46% having 11-15 years, and 0.75% with more than 15 years of experience.

OUTER MODEL RESULT

Convergent Validity

The level of convergent validity of each reflective measure is considered high if the correlation exceeds 0.70 with the construct being measured, indicating that the indicators consistently measure the construct of interest in this research**.**

Table 2 Outer Loading

Indicator	Outer Loading
X1_1	0,87
X1_2	0,81
X1_3	0,795
X1_4	0,713
X2_1	0,885
X2_2	0,858
X2_3	0,824
X2_4	0,796
X3_1	0,873
X3_2	0,87

Source: Author

Table 3 Outer Loading

Indicator	Outer Loading
X3_3	0,853
X3_4	0,865
X4_1	0,832
X4_2	0,87
X4_3	0,801
X4_4	0,85
X5_1	0,726
X5_2	0,815
X5_3	0,812
X5_4	0,731
X6_1	0,885
X6_2	0,875
X6_3	0,852
X6_4	0,847
Y_1	0,852
Y_2	0,839
Y_3	0,793
Y_4	0,755

Source: Author

The outer loading test results presented in Table indicate that all indicators have loading values exceeding 0.70. As a result, the data that met this criterion will be used for further testing.

Table 4 Average Variance Extracted (AVE)

Variable	Average Variance Extracted (AVE)	Information of Validity
Performance Expectancy (X1)	0.638	Valid
Effort Expectancy (X2)	0.708	Valid
Social Influence (X3)	0.749	Valid
Facilitating Conditions (X4)	0.703	Valid
Trust (X5)	0.596	Valid

Perceived Risk (X6)	0.748	Valid
Intention to Use (Y)	0.657	Valid

Source: Author

Table indicates that all variables have an AVE value greater than 0.50. This suggests that the study has achieved adequate convergent validity, as evidenced by both AVE and outer loading values.

Discriminant Validity

The extent to which a construct differentiates itself from other constructs is demonstrated by the discriminant validity test. Evaluating the cross loading and Fornell-Larcker criterion values can be used to conduct this test.

Table 5 Cross Loading

Indicator	X1	X2	X3	X4	X5	X6	Y
X1_1	**0,87**	0,512	0,513	0,562	0,6	-0,398	0,629
X1_2	**0,81**	0,342	0,351	0,512	0,468	-0,362	0,441
X1_3	**0,795**	0,317	0,337	0,466	0,338	-0,353	0,429
X1_4	**0,713**	0,348	0,182	0,433	0,415	-0,271	0,464
X2_1	0,399	**0,885**	0,285	0,46	0,483	-0,11	0,498
X2_2	0,426	**0,858**	0,327	0,553	0,488	-0,12	0,528
X2_3	0,376	**0,824**	0,233	0,435	0,446	-0,13	0,485
X2_4	0,44	**0,796**	0,371	0,493	0,542	-0,159	0,535
X3_1	0,46	0,301	**0,873**	0,356	0,468	-0,281	0,483
X3_2	0,362	0,404	**0,87**	0,409	0,53	-0,331	0,469
X3_3	0,36	0,309	**0,853**	0,428	0,476	-0,332	0,487
X3_4	0,375	0,246	**0,865**	0,378	0,415	-0,307	0,457
X4_1	0,561	0,504	0,342	**0,832**	0,51	-0,257	0,513
X4_2	0,576	0,532	0,378	**0,87**	0,453	-0,305	0,6
X4_3	0,431	0,358	0,366	**0,801**	0,441	-0,301	0,483
X4_4	0,512	0,532	0,433	**0,85**	0,481	-0,209	0,586
X5_1	0,358	0,361	0,388	0,369	**0,726**	-0,223	0,459
X5_2	0,483	0,438	0,438	0,36	**0,815**	-0,312	0,541
X5_3	0,483	0,548	0,467	0,521	**0,812**	-0,348	0,597
X5_4	0,469	0,437	0,388	0,462	**0,731**	-0,278	0,642
X6_1	-0,408	-0,137	-0,34	-0,234	-0,377	**0,885**	-0,282
X6_2	-0,372	-0,128	-0,302	-0,293	-0,315	**0,875**	-0,334
X6_3	-0,378	-0,185	-0,346	-0,34	-0,322	**0,852**	-0,367
X6_4	-0,348	-0,074	-0,252	-0,224	-0,302	**0,847**	-0,258
Y_1	0,496	0,446	0,451	0,598	0,578	-0,272	**0,852**
Y_2	0,622	0,563	0,403	0,613	0,623	-0,352	**0,839**

Y_3	0,441	0,457	0,403	0,46	0,46	-0,202	**0,793**
Y_4	0,459	0,498	0,516	0,435	0,687	-0,325	**0,755**

Source: Author

Table shows that each indicator's cross loading value for its own variable is higher than the cross-loading value of the other variables. Thus, it can be said that the discriminant validity of this research is good.

Table 6 Fornell-Larcker Criterion

Variable	Average Variance Extracted (AVE)	Fornell-Larcker Criterion
X1	0.638	0,799
X2	0.708	0,842
X3	0.749	0,865
X4	0.703	0,839
X5	0.596	0,772
X6	0.748	0,865
Y	0.657	0,811

Source: Author

Table shows that each contract's square root AVE is more than the correlation value, indicating that the research model's constructs still have good discriminant validity.

Reliability Test

The degree to which measurement outcomes using the same object result in the same data is known as the reliability test. Cronbach's alpha and composite reliability can be assessed to complete this test.

Table 7 Composite Reliability and Cronbach’s Alpha

Variable	Cronbach's alpha	Composite reliability	Information
Performance Expectancy (X1)	0,811	0,875	Reliable
Effort Expectancy (X2)	0,862	0,906	Reliable
Social Influence (X3)	0,888	0,923	Reliable
Facilitating Conditions (X4)	0,859	0,904	Reliable
Trust (X5)	0,774	0,855	Reliable
Perceived Risk (X6)	0,888	0,922	Reliable
Intention to Use (Y)	0,826	0,884	Reliable

Source: Author

Table shows that every variable has a Cronbach's alpha of better than 0.6 and a composite reliability of greater than 0.7. Consequently, it can be argued that this research is dependable because it satisfies the reliability test criteria.

Inner Model Result

The R-squared value and the appropriate T- and P-values, with minimum T- and P-values of 0.05, are computed using the bootstrapping technique (Ghozali, 2016). The proposed hypothesis might be accepted if the T-statistics data technique generates results that are acceptable.

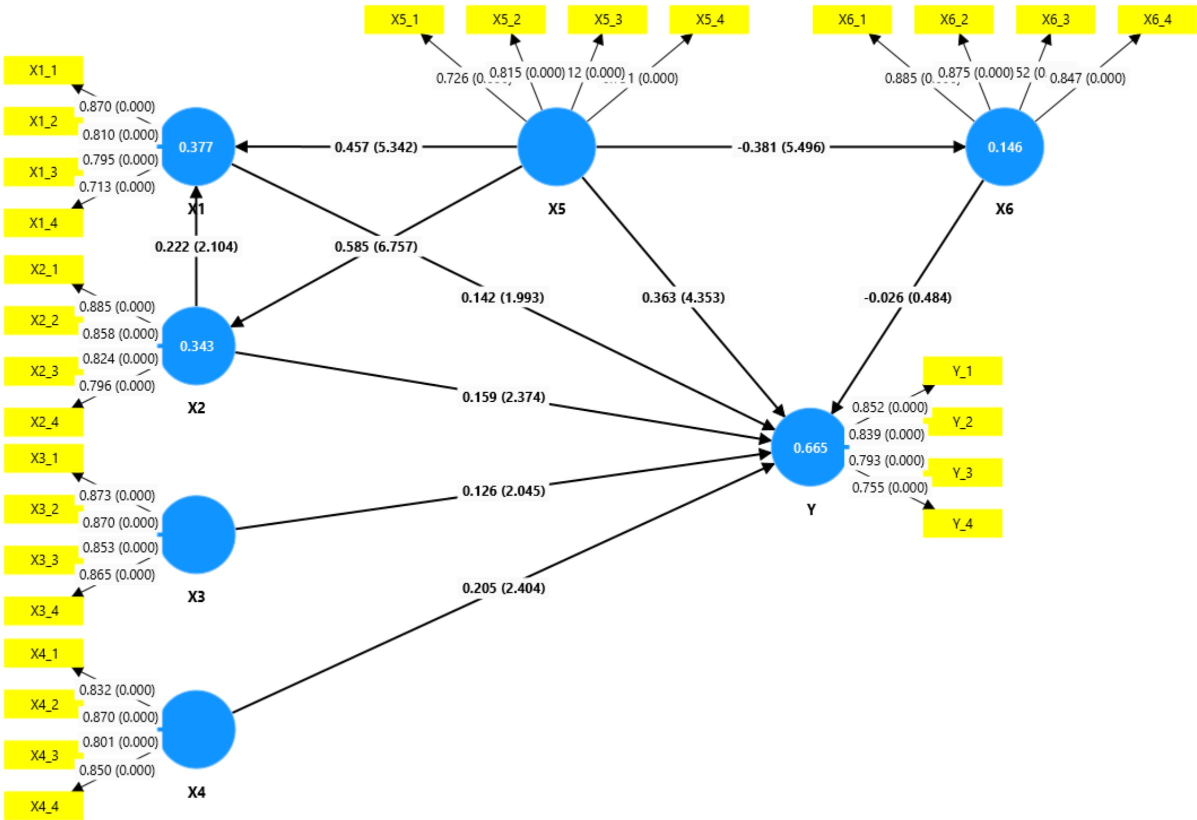

Figure 1 Bootstrapping

Coefficient of Determination (R2)

This coefficient has a value between 0 and 1. A lower value suggests that the independent variable's capacity to explain the dependent variable is getting progressively less effective (Ghozali, 2016). The R2 divided value into three categories: 0.67 (strong), 0.33 (moderate), and 0.19 (weak).

Table 8 R-Square (adjusted)

Variable	R-Square (adjusted)	Information
Performance Expectancy (X1)	0.368	Moderate
Effort Expectancy (X2)	0.338	Moderate
Perceived Risk (X6)	0.139	Weak
Intention to Use (Y)	0.649	Strong

Source: Author

The R-Square values reveal different levels of explanatory power. Performance expectancy is explained 36.8% by effort expectancy and trust, with the remaining 63.2% attributed to other factors, indicating a moderate explanation. Effort expectancy is explained 33.8% by trust, with 66.2% due to other factors, also reflecting a moderate explanation. Perceived risk is explained 13.9% by trust, with 86.1% due to other factors, showing a weak explanation. In contrast, intention to use is strongly explained 64.9% by performance expectancy, effort expectancy, social influence, facilitating conditions, trust, and perceived risk.

Hypothesis Test Results

In this research, hypothesis testing is employed to determine whether a previously proposed hypothesis may be accepted or rejected. The researchers employ the path coefficient value, t-statistics value, and p value as evaluation benchmarks while doing hypothesis analysis. To demonstrate the association between the variables, the t-statistics value larger than 1.96 and the significant level of p value less than 0.05 are utilized as reference criteria.

Table 9 Hypotheses Testing Result

Hypothesis	Relations Of Variable	Original sample (O)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Information
H1	**X1 -> Y**	0,142	0,071	1,993	0.046	Accepted
H2	**X2 -> Y**	0,191	0,071	2,672	0.008	Accepted
H3	**X2 -> X1**	0,222	0,106	2,104	0.035	Accepted
H4	**X3 -> Y**	0,126	0,061	2,045	0.041	Accepted
H5	**X4 -> Y**	0,205	0,085	2,404	0.016	Accepted
H6	**X6 -> Y**	-0,026	0,053	0,484	0.628	Rejected
H7	**X5 -> Y**	0,549	0,084	6,559	0,000	Accepted
H8	**X5 -> X1**	0,587	0,076	7,754	0,000	Accepted
H9	**X5 -> X2**	0,585	0,087	6,757	0,000	Accepted
H10	**X5 -> X6**	-0,381	0,069	5,496	0,000	Accepted

Source: Author

The researchers refer to the path coefficient value, t-statistics value, and p-value to decide whether to accept or reject the hypothesis throughout the hypothesis testing process. The test results show that nine hypotheses are acceptable, including three hypotheses: H1, H2, H3, H4, H5, H7, H8, H9, and H10. However, one theory, H6, is rejected.

The Effect of Performance Expectancy on Auditor Intention to Use Big Data Analytics

The data shows that performance expectancy significantly affects auditors' intention to use Big Data Analytics. Auditors are more inclined to adopt the technology if they believe it improves performance. Effective communication about the benefits of Big Data Analytics is essential for encouraging its adoption.

This finding is supported by Esawe et al. (2022) and Penney et al. (2021), who emphasize that a belief in performance improvement drives technology adoption. Cabrera-Sábrera & Villarejo-Ramos (2019) also indicate that positive perceptions of Big Data Analytics encourage its use. Furthermore, Pedrosa et al. (2020) and Al-Hiyari et al. (2019) show that auditors prefer tools like CAATs to anticipate better efficiency and performance.

The Effect of Effort Expectancy on Auditor Intention to Use Big Data Analytics

Effort expectancy significantly impacts auditors' intention to use Big Data Analytics. Auditors are more likely to adopt software that they perceive as easy to use and requiring minimal effort. This emphasizes the importance of user-friendly technology, particularly in the fast-paced auditing environment, where efficiency and accessibility are crucial. Technologies with a low learning curve and straightforward operation are more attractive to auditors.

This finding aligns with research from Esawe et al. (2022) and Penney et al. (2021), which highlight that ease of use enhances technology adoption. This effect is also supported by research from Yosephine et al. (2019), Kim et al. (2016), and Curtis and Payne (2014), which indicates that user-friendly audit software is more likely to be adopted. However, contrasting studies by Ferri et al. (2020) and Pedrosa et al. (2020) suggest that effort expectancy may be less influential for more complex tools like CAATs and Blockchain, due to their specialized requirements and limited use cases, which might deter less experienced auditors.

The Effect of Effort Expectancy on Performance Expectancy

The research data show that effort expectancy significantly affects performance expectancy. Auditors are more inclined to adopt Big Data Analytics when they find it easy to use and require minimal effort. An intuitive and user-friendly design promotes faster adoption and strengthens the belief that the technology will enhance performance.

This aligns with studies by Penney et al. (2021), Alalwan et al. (2017), and Tan & Lau (2016), which suggest that when technology is perceived as easy and low-effort, users expect more significant performance benefits. For auditors, a technology that is simple and efficient is viewed as more valuable. Thus, improving ease of use and providing practical training can boost adoption and enhance perceived performance.

The Effect of Facilitating Conditions on Auditor Intention to Use Big Data Analytics

Facilitating conditions significantly impact auditors' intention to use Big Data Analytics. When auditors have strong support, including adequate hardware, software, training, IT support, and favorable company policies, they are more confident and willing to adopt the technology.

This finding is consistent with research by Cabrera-Sábrera and Villarejo-Ramos (2019) and Alawan et al. (2017), which underscores the importance of facilitating conditions in technology adoption. Yosephine et al. (2019) also highlight that providing essential resources and support enhances the intention to use technologies like GAS. Moreover, studies on CAATs by Al-Hiyari (2019) demonstrate that technical and financial support boosts the likelihood of using audit software.

The Effect of Social Influence on Auditor Intention to Use Big Data Analytics

The research indicates that social influence significantly affects auditors' intention to use Big Data Analytics. Strong social influence from sources such as coworkers, superiors, clients, and professional communities increases auditors' motivation to adopt new technologies. Support from respected figures and client demands can drive auditors to embrace Big Data Analytics, influenced by both the technology's benefits and the perception of others' views.

This finding is supported by Penny et al. (2021) and Esawe et al. (2022), who highlight that social influence enhances technology adoption when peer advice is valued. Ferri et al. (2020) also note that endorsement by social groups encourages technology use. However, Al-Hiyari et al. (2019) found that social pressure did not affect CAAT adoption in Jordan, suggesting that the impact of social influence can vary by cultural and contextual factors.

The Effect of Perceived Risk on Auditor Intention to Use Big Data Analytics

The research shows that perceived risk does not significantly influence auditors' intention to use Big Data Analytics. Auditors are generally inclined to use the technology despite their risk perceptions, likely due to supportive work environments, such as operational and IT support, which mitigate concerns. Additionally, extensive training and guidance help auditors integrate Big Data Analytics effectively, reducing perceived risk.

This finding aligns with Cabrera-Sábrera & Villarejo-Ramos (2019), who also noted minimal impact of perceived risk on technology adoption. In contrast, Penney et al. (2021) and Martins et al. (2014) suggest that perceived risk can deter technology adoption. This discrepancy might arise from the different contexts of public versus corporate environments, where auditors benefit from more support and training. Enhancing confidence through a supportive work environment is crucial for promoting the adoption of Big Data Analytics.

The Effect of Trust on Auditor Intention to Use Big Data Analytics

The study finds that trust significantly impacts auditors' intention to use Big Data Analytics. Auditors are more likely to adopt and rely on the technology when they trust its accuracy, reliability, and ability to meet their needs. Confidence in the technology's ability to handle and analyze data effectively is crucial for ensuring its use in decision-making.

This aligns with findings by Esawe et al. (2022) and Alalwan et al. (2017), which emphasize that trust is a significant factor in technology adoption. Trust not only predicts the intention to use technology but also encourages ongoing use. Chao (2019) supports this, noting that higher trust enhances technology adoption. Similarly, Almagrashi et al. (2023) found that trust in CAATs directly influences their use, as confidence in their reliability and accuracy motivates auditors to adopt them for more effective financial analysis.

The Effect of Trust on Effort Expectancy

The data processing results indicate that trust significantly affects effort expectancy. When auditors trust that Big Data Analytics is user-friendly and well-supported, they expect it to require minimal effort and be easy to use. This trust lowers their perceived effort expectancy, as they anticipate learning and using the technology will be straightforward.

This finding aligns with research by Penney et al. (2021) and Alkali & Mansor (2017), which demonstrate that trust enhances perceived ease of use. For auditors, confidence in the technology's reliability and ability to meet their needs, such as ease of data access and integration, leads to higher acceptance. High trust ensures that auditors believe the technology will simplify their tasks rather than complicate them

The Effect of Trust on Performance Expectancy

The research data indicates that trust significantly influences performance expectancy. Auditors who trust Big Data Analytics are likelier to believe it will enhance their performance, leading to more effective and efficient work. When auditors have confidence in the technology's reliability and accuracy, their expectations of its benefits increase, which boosts their motivation to adopt it.

This finding aligns with Alkali & Mansor (2017), showing that trust enhances perceived technology benefits and influences user attitudes. Similarly, Alawan et al. (2016) found a strong correlation between trust and performance expectations, indicating that confidence in technology enhances its perceived productivity. High trust in Big Data Analytics helps auditors embrace its potential, improving audit performance.

The Effect of Trust on Perceived Risk

The research findings reveal that trust significantly impacts perceived risk. Auditors' concerns about data security and privacy are alleviated when they have confidence in the technology and its providers. Building this trust involves obtaining security certifications and ensuring data management and protection transparency. By addressing these concerns, service providers can reduce perceived risks and encourage the adoption of Big Data Analytics.

This aligns with studies by Penney et al. (2021), Koksal (2016), and Wang & Lin (2016), which demonstrate that trust lowers perceived risks. Effective trust-building measures, such as robust security practices and clear communication, help mitigate the uncertainties associated with technology, making adoption more feasible.

SUMMARY

The investigation verifies that trust and facilitating conditions are crucial in auditors' intention to implement BDA, whereas performance expectancy and effort expectancy enhance perceived benefits and ease of use. Social influence significantly enhances adoption via peer and client expectations, although perceived risk had little deterrent effects owing to robust organizational support. These findings highlight the necessity of cultivating a supportive atmosphere and establishing trust to improve BDA adoption among Indonesian auditors.

CONCLUSION

This study emphasizes the substantial impact of performance expectancy, effort expectancy, social influence, facilitating conditions, and trust on auditors' intention to adopt Big Data Analytics (BDA). Trust became a vital facilitator, diminishing perceived risk, augmenting usability, and bolstering auditors' faith in the technology's dependability and efficacy. Performance expectancy and effort expectancy influenced perceptions of efficiency and usefulness, whereas social influence and facilitating conditions, including infrastructure and training, additionally encouraged uptake. The perceived danger had negligible influence, perhaps alleviated by robust organizational support and protective measures. The study's conclusions are constrained by its geographical concentration on Jakarta and dependence on self-reported data, potentially impacting generalizability. The practical ramifications necessitate audit companies and technology providers to establish training programs, create user-friendly platforms, and foster confidence through transparent methods. Future research should examine the long-term impacts of BDA adoption and evaluate its implementation across many industries and countries to improve comprehension and scalability.

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