International Journal of Artificial Intelegence Research
Vol. 8, No. 1.1 (2024)
ISSN 2579-7298

Influence of Audit Technology Implementation on Efficiency and Accuracy of Audits in Public Companies: A Case Study of Manufacturing Companies in Indonesia

Raden Nasution[1*], Dailibas[2], Chaerudin[3], Muhammad Nasim Harahap[4], Ali Mutaufiq[5], Destiana Kumala[6]

[1*,2,3,4] Faculty of Economics, Singaperbangsa University, Karawawang, West Java, Indonesia
[5]STIE Bisnis Internasional Indonesia, Bekasi, Indonesia
STEBIS Bina Mandiri, Bogor, West Java, Indonesia
[1*]r.nasution@fe.unsika.ac.id, [2]dailibas@fe.unsika.ac.id, [3]chairudin@fe.unsika.ac.id, [4]muhammad.nasim@feb.unsika.ac.id, [5]alimutaufiq999@gmail.com, [6]destiana.kumala@binamandiri.ac.id

ARTICLE INFO

Article history
Received
Revised
Accepted

Keywords
Application of Audit Technology
Efficiency Audits

ABSTRACT (10PT)

This research discusses the influence of the application of audit technology on audit efficiency and accuracy in manufacturing companies in Indonesia. This research uses a type of quantitative research with a survey approach with the method used is saturated sampling/census, with a sample of 26 manufacturing companies in Indonesia. This research data analysis technique uses PLS software version 3.0 (Partial Least Square). The results of the research showed that the application of audit technology had a positive and significant effect on efficiency with a statistical t value of 31.066 > 2.055 and a P-value of 0.000, this means that techniques for implementing audit technology such as audit information systems , big data analytics. , and AI (artificial intelligence) technology can significantly improve the efficiency of the audit process. This technology allows auditors to conduct deeper analysis of transaction data and complex patterns, identifying anomalies or potential risks more quickly and precisely. The application of audit technology has a positive and significant effect on audit accuracy with a statistical t value of 76.415 > 2.055 and a P-value of 0.000, this means that accurately, audit technology can also minimize human error in the audit process, because it can carry out automatic testing and broader analysis of available data. This increases the accuracy of the financial reports produced, which is one of the main objectives of the audit process in supporting transparency and public trust in public companies.

1. Introduction

A manufacturing company is a business entity that produces physical goods by changing or processing raw materials into finished products through a series of production processes. The production process in manufacturing involves steps such as design, production, assembly, and packaging of the product. A manufacturing company audit is a comprehensive examination and assessment of the entire function to determine whether it is running according to procedures and determine whether the performance is satisfactory. In this era of increasingly advanced technology, manufacturing companies have a significant role in meeting society's needs.

In an era of business that continues to grow rapidly, the use of technology-based accounting information systems to transform audits has become a top priority. Companies must manage their financial data more effectively and accurately as economic complexity and globalization increase.

With the adoption of the right technology, financial information can be accessed more quickly and accurately, enabling internal and external parties to better understand the company's financial performance and position. (Syahputra, & Budiman, 2021).

Many aspects of human life have changed due to advances in Artificial Intelligence (AI) technology, including the fields of accounting and auditing. AI can speed up the audit process by completing tasks that previously took a long time and manually quickly and accurately, for example how AI technology processes data automatically and analyzes the risks associated with that data.

By using AI technology, auditors can save time in carrying out their work, thereby increasing audit productivity and efficiency. The use of AI to improve operational efficiency has been proven to improve company performance and competitiveness. However, to implement AI technology successfully, companies need to pay attention to existing challenges and develop appropriate strategies to overcome them. (Novita and Zahra, 2024)

The application of artificial intelligence (AI) in manufacturing companies can increase operational efficiency in various ways. First, AI allows companies to optimize supply chains by predicting demand, managing inventory, and planning production more accurately (Arinez et al., 2020)

But the use of AI technology in the audit process also has adverse effects. One of the problems that arises is that the public does not trust the results of audits carried out with AI. Some people still doubt AI's ability to perform audit tasks that should be carried out by humans, such as evaluating a company's sustainability feasibility and risk analysis.

Additionally, the use of AI could compromise the work of human auditors. AI technology can replace human auditors' duties at certain points, such as data collection and risk analysis, thereby reducing the number of auditors required for a company. As a result, human auditors can lose their jobs and lose the skills they need to run the audit process.

Based on the phenomena and problems above, researchers are interested in conducting research entitled The Effect of Implementing Audit Technology on Audit Efficiency and Accuracy in Public Companies: Case Study of Manufacturing Companies in Indonesia.

2. Method

Hypothesis testing in this research was carried out using the Partial Least Square (PLS) method. PLS is a very powerful analysis method because it does not require data assumptions using a specific measurement scale or large sample sizes. This method is suitable for use in causal predictive analysis in complex situations and when theoretical support is low. PLS allows researchers to draw more accurate conclusions even under limited conditions.

Research population refers to the entire group of individuals, events, or other relevant things that researchers can use to draw conclusions (Sekaran & Bougie, 2016). In the context of this research, the population selected is manufacturing companies in Indonesia in the food and beverage industry sub-sector listed on the Indonesia Stock Exchange (BEI) in 2023-2024. There are 26 companies in this sub-sector, and the following is a list of these companies:

Table 1. List of Manufacturing Companies in Indonesia, Food and Beverage Industry Sub-Sector Listed on the IDX in 2023-2024

No	Multinational Company Name
1	Tiga Pilar Sejahtera Food Tbk, PT (AISA)
2	Tri Banyan Tirta Tbk, PT (ALTO)
3	Campina Ice Cream Industry Tbk, PT (CAMP)
4	Wilmar Cahaya Indonesia Tbk, PT (CEKA)
5	Sariguna Primatirta Tbk, PT (CLEO)
6	Wahana Interfood Nusantara Tbk, PT (COCO)
7	Delta Djakarta Tbk (DLTA)
8	Diamond Food Indonesia Tbk, PT (DMND)
9	Sentra Food Indonesia Tbk, PT (FOOD)
10	Garudafood Putra Putri Jaya Tbk, PT (GOOD)
11	Buyung Poetra Sembada Tbk, PT (HOKI)

12	Indofood CBP Sukses Makmur Tbk, PT (ICBP)
13	Era Mandiri Cemerlang Tbk (IKAN)
14	Indofood Sukses Makmur Tbk, PT (INDF)
15	Mulia Boga Raya Tbk, PT (KEJU)
16	Multi Bintang Indonesia Tbk, PT (MLI)
17	Mayora Indah TBK, PT (MYOR)
18	Pratama Abadi Nusa Industri Tbk, PT (PANI)
19	Prima Cakrawala Abadi Tbk (PCAR)
20	Prashida Aneka Niaga Tbk, PT (PSDN)
21	Palma Serasih Tbk, PT (PSGO)
22	Nippon Indosari Corporindo Tbk, PT (ROTI)
23	Sekar Bumi Tbk, PT (SKBM)
24	Sekar Laut Tbk, PT (SKLT)
25	Siantar Top Tbk, PT (STTP)
26	Ultrajaya Milk Industry and Trading Company Tbk, PT (ULTJ)

Source: BEI-2024

So, the population in this study was 26 manufacturing companies in the food and beverage industry sub-sector. According to Sugiyono (2011:81), the sample is part of the number and characteristics of the population. If the sample size is not representative, then the research results cannot represent the population. For example, due to limited funds, personnel and time, researchers can use samples taken from the population. What is learned from the sample, the conclusions can be applied to the population in general. Therefore, samples taken from the population must be truly representative.

In this research, the sample used was the entire population, namely 26 manufacturing companies in the food and beverage industry sub-sector. The sampling technique used in this research is the Saturated Sampling or Census method. According to Sugiyono (2016: 85), "Saturated sampling is a sampling technique when all members of the population are sampled. Another term for a saturated sample is census, where the entire population is sampled." By using this method, all companies included in the population are used as research samples, ensuring that all relevant data can be analyzed to draw accurate and comprehensive conclusions.

The data analysis technique for this research uses PLS software version 3.0 (Partial Least Square), which is a variant-based structural equation analysis (Structural Equation Model) which can simultaneously test the measurement model as well as test the structural model. From the research results collected, the following analysis methods will be available:

a. Measurement Model (Outer Model

The measurement model (outer model) was carried out to test the validity and reliability of the research instrument. The validity test in this research uses convergent validity and discriminant validity. Convergent validity is seen from the measurement model with reflection indicators which are assessed based on the correlation of the model between the component score/item score and the construct score calculated using PLS. If the correlation is more than 0.70 with the construct to be measured, the individual reflection measure is said to be high. For early stage research, measurements with an outer loading value of 0.5-0.6 are considered sufficient.

Ghozali (2015:114) explains that in assessing dicriminant validity using another method, it is comparing the square root of average variance extracted (AVE) value. The recommended value is that the AVE value must be greater than 0.5. The AVE formula according to Ghozali (2015:115) is:

$$\mathbf{AVE = \lambda i2\ \lambda i2 + ivar\ (\varepsilon i)}$$

The recommended composite reliability value must be above 0.6 (Ghozali, 2015: 115).

b. Structural Model (Inner Model)

Structural models are used to predict causal relationships between latent variables. The structural model was evaluated by looking at the percentage of variance explained by the R2 value for the dependent variable using the Stone-Geisser Q-Square Test (Ghozali, 2015: 117). The equation model is:

$$\mathbf{N = \beta O + \beta\eta + \eta\varepsilon + \zeta}$$

Whereηdescribes the vector of endogenous (dependent) latent variables,εis a vector of residual variables. Each dependent latent variable of the latent variable can be specified as follows:

$$pc = \Sigma i \beta J i \eta i + \Sigma i \gamma j b \varepsilon b + \zeta j$$

Whereβji andγjb is the path coefficient that connects the endogenous predictor and the exogenous latent variableεAndηalong the index range i and b, andζis the inner residual variable. If the results produce an R2 value greater than 0.2, it can be interpreted that the latent predictor has a large structural level influence. The following is an image of the research structural model:

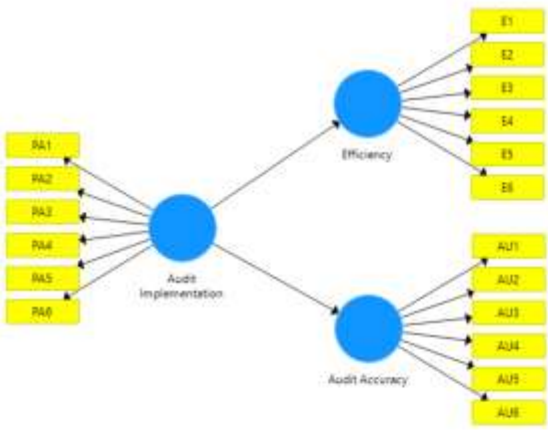

Fig. 1. Research Model

c. Hypothesis test

Hypothesis testing (β, γ, and λ) was carried out using the bootstrap resampling method developed by Geisser & Stone (Ghozali, 2015). According to Jogiyanto and Abdillah (2015:55) the significance measure of hypothesis support can be used by comparing the t table and t statistic values through the following decision making criteria:

1) If t statistic > t table and p value < sig 0.05, it means Ha is accepted, Ho is rejected.
   If t statistic ≤ t table and p values ≥ sig 0.05 means Ha is rejected, Ho is accepted

1. Outer Model Analysis

Testing the measurement model (outer model) is used to determine the specifications of the relationship between latent variables and their manifest variables. This test includes convergent validity, discriminant validity and reliability.

a. Convergent Validity

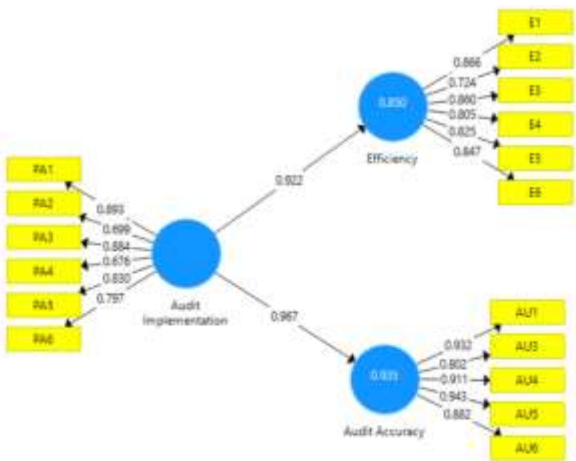

Fig. 2. Outer Model, Algorithm Testing

According to Ghozali (2018:25) a correlation can be said to meet convergent validity if it has a loading value of > 0.7. The output shows that the loading factor provides a value above the recommended value, namely 0.7. However, at the research scale development stage, a loading of 0.60 is still acceptable. So that the indicators used in this research have met convergent validity.The structural model in this research is shown in the following figure:

Table 2. Outer Loading

	Technology Implementation Audit	efficiency	Accuracy Audit
AU1			0.932
AU3			0.802
AU4			0.911
AU5			0.943
AU6			0.882
E1		0.866	
E2		0.724	
E3		0.860	
E4		0.805	
E5		0.825	
E6		0.847	
PA1	0.893		
PA2	0.699		
PA3	0.884		
PA4	0.676		
PA5	0.830		
PA6	0.797		

[a.] Source: Smart PLS Program Output. 3.0, 2024

Based on the data in table 2, it can be seen that the lowest outer loading value in the outer model test results of this research is 0.676 in the PA4 dimension/Application of Audit Technology. Referring to the previously determined outer loading limit, namely 0.7, however, at the scale development stage research, a loading of 0.60 is still acceptable. So these results show that the model meets the assumption of convergent validity because the lowest outer loading value is 0.676 > 0.6.

b. Construct Validity and Reliability

Table 3. Construct Validity and Reliability

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Implementation Technology Audit	0.885	0.892	0.914	0.641
efficiency	0.904	0.904	0.926	0.677
Accuracy Audit	0.937	0.940	0.953	0.802

[b.] Source: Smart PLS Program Output. 3.0, 2024

From the data in Table 3 above, it is known that the lowest AVE value of the 3 variables is 0.641, which is the variable for developing the application of audit technology. These results indicate that the three research variables have met the discriminant validity assumption because the lowest AVE value obtained was more than 0.5. Meanwhile, in the results of Cronbach alpha and composite reliability, it is known that the lowest values are 0.885 and 0.892, which are owned by the audit technology implementation variable. Thus, these results also prove that all variables meet the construct reliability assumptions because the lowest Cronbach alpha and composite reliability values are > 0.7.

2. Inner Model Testing

After testing the outer model, it is then necessary to evaluate the final structural equation model (inner model). The inner model test for this research was carried out by looking at the path coefficient and R square values as follows:

Table 4. R Square

	R Square	R Square Adjusted

efficiency	0.850	0.844
Accuracy Audit	0.935	0.933

[c] Source: Smart PLS Program Output. 3.0, author processed data in 2024

Based on table 4 above, it shows that the R Square value for the efficiency variable is 0.850. This result explains that the efficiency percentage is 85%. This means that the variable application of audit technology influences efficiency by 85% and the remaining 15% is influenced by other variables, while the R Square value for the audit accuracy variable is 0.935. This result explains that the percentage of audit accuracy is 93.5%. This means that the variable application of audit technology influences audit accuracy by 93.5% and the remaining 6.5% is influenced by other variables.

Table 5. Inner Model test results

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Audit Technology Implementation -> Efficiency	0.922	0.924	0.030	31,066	0,000
Technology Implementation Audit -> Accuracy Audit	0.967	0.969	0.013	76,415	0,000

[d] Source: Smart PLS Program Output. 3.0, author processed data in 2024

Based on table 5 above, the results of the partial evaluation of the structural equation model of the relationship between variables which are explained by the path coefficient value can be described as follows:

1) The path coefficient for hypothesis 1, namely the variable application of audit technology on efficiency, was obtained at 0.922. This value shows that there is an influence of 92.2% (0.922 x 100%). These results mean that implementing good audit technology can increase efficiency.
2) The path coefficient value in hypothesis 2 was obtained at 0.967. This value shows that the application of audit technology has an influence of 96.7% (0.967 x 100%) on audit accuracy. This result also means that the better the implementation of audit technology, the higher the audit accuracy.

3. Hypothesis test

This research has 2 hypotheses as research questions that have been formulated and need to be tested for truth. Hypothesis testing in this study uses the t test, namely by comparing the statistical t value obtained from the bootstrapping test with the critical limit of the t table value of 2.055 at a significance level of 5% (0.05). The results of this research hypothesis test are presented as follows:

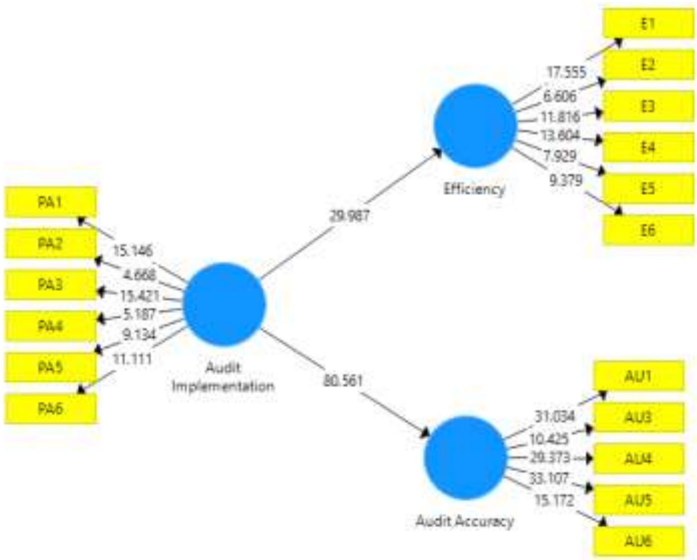

Fig. 3. Inner Model, Bootstrapping Testing

Table 6. Direct Effect Test Results

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Note
Audit Technology Implementation -> Efficiency	0.922	0.924	0.030	31,066	0,000	Accepted
Technology Implementation Audit -> Accuracy Audit	0.967	0.969	0.013	76,415	0,000	Accepted

e. Source: Smart PLS Program Output. 3.0, author processed data in 2024

Based on the PLS output (bootstrapping test) presented in Table 6, it can be explained that:

1. Hypothesis 1: From the original sample value of 0.922, the t statistic value is 31.066 > 2.055 and the P-value is 0.000. These results prove that the application of audit technology has a positive and significant effect on efficiency with a relationship value of 92.2% (0.922 x 100%). The t statistic value of 31.066 > t table 2.055 and P-value 0.000 < 0.05 proves that hypothesis 1 in this study is accepted
2. Hypothesis 2: From the original sample value of 0.967, the t statistic value is 76.415 > 2.055 and the P-value is 0.000. These results prove that the application of audit technology has a positive and significant effect on audit accuracy with a relationship value of 96.7% (0.967 x 100%). The t statistic value of 76.415 > t table 2.055 and P-value 0.000 < 0.05 proves that hypothesis 2 in this study is accepted.

3. Conclusion

Based on the results of the research that has been carried out and the data analysis explained in the previous chapter, several conclusions can be drawn as follows:

There is a positive and significant influence from the application of audit technology on efficiency. The statistical t value obtained is 31.066, which is much greater than the critical value of 2.055, and the P-value of 0.000 indicates high significance. This means that the application of audit technology, such as audit information systems, big data analytics, and artificial intelligence (AI) technology, significantly increases the efficiency of the audit process. This technology allows auditors to conduct deeper analysis of transaction data and complex patterns, identifying anomalies or potential risks more quickly and precisely. Thus, companies that adopt this technology can reduce the time and resources required to complete audits, while increasing the precision and reliability of the audit process itself.

Apart from that, the application of audit technology also has a positive and significant effect on audit accuracy. The statistical t value of 76.415 which is greater than the critical value of 2.055 and the P-value of 0.000 indicates that audit technology can minimize human error in the audit process. Audit technology enables automated testing and broader analysis of available data, which in turn increases the accuracy of the resulting financial reports. This accuracy is one of the main objectives of the audit process, because it supports transparency and public trust in the company's financial reports. With greater accuracy, companies can ensure that the information they provide to stakeholders is more trustworthy and valid, which is critical in an increasingly complex and highly regulated business environment.

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