ARTIFICIAL NEURAL NETWORK METHODOLOGY IN FINANCIAL STATEMENTS FRAUD: AN EMPIRICAL STUDY IN THE PROPERTY AND REAL ESTATE SECTOR

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Abstract

Financial statements are crucial reports for stakeholders to assess a company's financial condition. However, they are susceptible to fraud, with financial statement fraud representing the type with the largest losses in 2024, amounting to $766,000 (Association of Certified Fraud Examiners [ACFE], 2024). In response to this significant issue, the International Federation of Accountants (IFAC, 2009) issued the International Standard on Auditing (ISA) 240, which highlights three factors contributing to fraud: 1) pressure, 2) opportunity, and 3) rationalization, known as the fraud triangle. This study aims to analyze the impact of these fraud triangle factors on financial statement fraud in property and real estate sector companies listed on the stock exchanges of the Association of Southeast Asian Nations (ASEAN) countries during the 2021–2022 period. The study population comprises property and real estate companies in ASEAN, with a sample size of 170 companies, totaling 340 observations over a two-year period. Secondary data were collected from the OSIRIS database, and a purposive sampling technique was used. The data analysis method involved an artificial neural network (ANN) analysis with IBM SPSS 25 software. The prediction results showed an accuracy level of 81.3 percent. This study provides empirical evidence that pressure, opportunity, and rationalization significantly influence financial statement fraud, supporting the fraud triangle theory in explaining this phenomenon.

Keywords: Association of Southeast Asian Nations, Artificial Neural Network, Fraud Triangle, Financial Statement Fraud, Property and Real Estate

Authors' individual contribution: Conceptualization — D.V.R.W.R. and R.W.; Methodology — D.V.R.W.R. and R.W.; Formal Analysis — D.V.R.W.R. and R.W.; Investigation — D.V.R.W.R. and R.W.; Data Curation — D.V.R.W.R. and R.W.; Writing — Original Draft — D.V.R.W.R. and R.W.; Writing — Review & Editing — D.V.R.W.R. and R.W.; Visualization — D.V.R.W.R. and R.W.

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1. INTRODUCTION

Financial reports are detailed, objective, and reliable information media used to communicate the company's economic activities and financial performance to stakeholders (Osadchy et al., 2018). These reports must be presented according to actual conditions, reflecting normal conditions, growth, or crisis situations in the company. However, in reality, some companies engage in fraudulent practices by presenting misleading information to users of financial reports to create an image of continuous financial improvement. This act is commonly referred to as financial statement fraud (Achmad et al., 2022). The causes of financial statement fraud can be explained through agency theory, which describes the contractual relationship between shareholders (principals) and management (agents). Challenges in maintaining this contract arise because agents tend to prioritize their own interests, one of which includes manipulating financial statements to enhance the company's performance (Naldo & Widuri, 2023).

According to the Association of Certified Fraud Examiners (ACFE) (2024), the greatest losses were found in financial statement fraud, representing 5% of cases and resulting in an average loss of $766,000, compared to other fraud types such as corruption (48%) of cases with an average loss of $2,000,000 and asset misappropriation (89%) of cases with an average loss of $120,000. The ACFE (2024) report also highlights that fraud losses in the Asia-Pacific (APAC) region were the highest, with an average loss of $1,200,000 across 183 cases, of which 6% were related to financial statement fraud. These losses can harm investors, creditors, and other stakeholders impacted by these fraud cases, eroding trust and damaging overall market integrity. Of the 183 fraud cases in the APAC region, 45% were found in Association of Southeast Asian Nations (ASEAN) countries. Various factors contribute to the prevalence of fraud in Southeast Asia, such as companies facing challenges amidst market competition, political factors, and global economic uncertainties post-COVID-19 (Jan, 2018). This claim is supported by a study by Naldo and Widuri (2023), which revealed that 44.9% of companies in ASEAN, out of a sample of 345, engaged in financial statement fraud. This percentage indicates the serious impact of financial statement fraud, making ASEAN countries an interesting area to study, as historical data and prior research suggest a tendency for companies in ASEAN to commit financial reporting fraud, with such countries bearing significant losses due to these fraudulent activities.

An example of financial statement fraud in an ASEAN country is the case of PT Bakrieland Development Tbk, which engaged in financial statement fraud related to its liabilities in 2018. An audit by Kosasih, Nurdiyaman Tjahjo, and Partners revealed a significant discrepancy: actual liabilities amounted to Rp 16.13 trillion, considerably higher than the reported amount of Rp 6.2 trillion (Ayuningtyas, 2019). Consequently, the company received a warning from the Indonesia Stock Exchange (IDX), which suspended its stock trading and imposed a fine of Rp 150 million for delayed reporting and fine payment (Ayuningtyas, 2019). As this example illustrates, financial statement fraud can occur in the property and real estate sectors. According to the ACFE (2022), this sector ranks highest in terms of victim organizations. Additionally, the property and real estate sector is vulnerable to corruption, bribery, procurement fraud, and tax evasion, which can impact financial reporting (Damayani et al., 2017). In 2018, there were 35 cases of fraud with a median loss of $180,000, rising to 52 cases with losses of $254,000 in 2020 and 41 cases with losses of $435,000 in 2022 (ACFE, 2022).

To simplify the detection of financial statement fraud, the International Federation of Accountants (IFAC) (2009) outlines three factors associated with fraud, based on the fraud triangle theory. The fraud triangle consists of pressure, opportunity, and rationalization (Cressey, 1954). The fraud triangle remains widely used by practitioners as an approach to fraud detection, and its popularity in detecting financial statement fraud has led to it becoming the foundation of audit policies both nationally and internationally (Homer, 2020). The fraud triangle offers a financial statement fraud detection model with a predictive accuracy of 73% (Skousen et al., 2009). There has been a lot of research on financial statement fraud, but only a few have used data mining techniques (15%) (Shahana et al., 2023). One data mining technique for detecting financial statement fraud is the artificial neural network (ANN) analysis method (Omar et al., 2017). The ANN method involves modeling the relationship between input and output by constructing a mathematical model that recognizes patterns within the sample data, such as correlations between seemingly unrelated data. The resulting model, when applied to new input data, produces output projections (Cerullo & Cerullo, 1999). ANN was chosen for its superior prediction accuracy of 94.87% in detecting financial statement fraud compared to traditional statistics, linear regression (92.4%), and other techniques (Omar et al., 2017). A study by Temponeras et al. (2019) also applied a predictive model using ANN to detect fraudulent financial statements (FFS) for companies in Greece, achieving a high reliability of 93.7% with a sample accuracy of 91.7%. However, contrasting with the study by Kirkos et al. (2007), their results indicated that logistic regression achieved an accuracy of 99% in detecting financial statement fraud, outperforming ANN and decision trees.

Due to the differing accuracy levels of the ANN method in detecting financial statement fraud, the researcher is interested in studying the effect of fraud triangle factors in detecting financial statement fraud using ANN in the property and real estate sectors on the ASEAN Stock Exchange in 2021–2022. The purpose of this research is to analyze:

RQ1: Does pressure, as proxied by the solvency ratio representing bankruptcy threats, significantly influence corporate financial statement fraud when using the artificial neural network method?

RQ2: Does opportunity, represented by accounts that are difficult to control and ineffective monitoring, significantly influence corporate financial statement fraud when using the artificial neural network method?

RQ3: Does rationalization, as proxied by the profitability ratio to observe aggressive and unrealistic profit trends, significantly influence corporate financial statement fraud when using the artificial neural network method?

This research offers both empirical and theoretical contributions. The empirical findings suggest that each fraud triangle factor based on the International Standard on Auditing (ISA) 240 influences the detection of financial statement fraud in the ASEAN property and real estate sector. This can assist companies in improving financial report quality and enhancing investor and stakeholder trust, thus minimizing errors in decision-making and supporting more effective and efficient operations. The theoretical findings contribute to the development of theories regarding factors that influence the success of data mining techniques in detecting financial statement fraud. The results of this study can provide a better understanding that financial ratios effectively represent fraud triangle factors to detect financial statement fraud, thereby aiding in the theoretical development of financial statement fraud detection.

The rest of this research is organized as follows. Section 2 provides the literature review. Section 3 covers the research methodology, Sections 4 and 5 discuss the results and Section 6 outlines the conclusion of the research.

2. LITERATURE REVIEW

2.1. Financial statement fraud

The ACFE (2024) report shows that among the three categories of occupational fraud, financial statement fraud causes the greatest losses globally compared to corruption and asset misappropriation. According to ACFE (2022), occupational fraud is a type of fraud committed by individuals within an organization or company. Financial statement fraud is particularly concerning as it results in the greatest losses for investors. There are several schemes for financial statement fraud, such as the destruction of documents based on accounting records, deliberate misrepresentation of events or transactions within financial statements, and the intentional application of incorrect accounting principles regarding regulation, classification, presentation, or disclosure (Ozcelik, 2020). This type of fraud undermines the integrity of financial information, impacting financial statement users such as investors, creditors, and auditors.

2.2. Fraud triangle

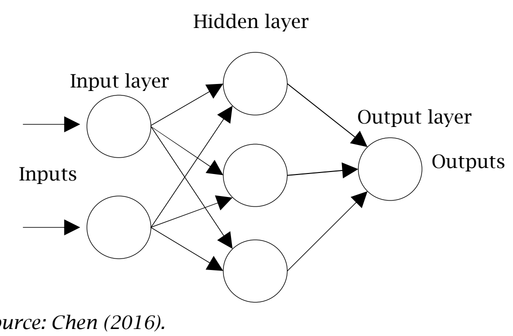
Fraud does not just happen in a company. However, to find out the cause, prevention and detection are carried out as early as possible. The fraud triangle serves as a foundational framework in fraud prevention and detection and is widely used as a theoretical basis in fraud literature (Albrecht, 2014; Cheliatsidou et al., 2023). The concept of the fraud triangle is outlined in the ISA 240 audit standard, which includes three primary elements: 1) pressure, 2) opportunity, and 3) rationalization (IFAC, 2009; Cheliatsidou et al., 2023). According to the fraud triangle theory developed by Donald R. Cressey (2009), all three elements must be present to motivate someone to commit fraud (Sánchez-Aguayo et al., 2022). Omar et al. (2017) describe pressure as a person's motivation to commit fraud, often related to financial concerns. Individuals facing financial pressure may attempt to solve their issues independently, increasing their susceptibility to fraud. The second element, opportunity, arises from weaknesses in internal controls, allowing fraudsters to exploit these gaps within an organization. The third element, rationalization, refers to how fraudsters justify their actions, perceiving them as neither illegal nor morally wrong. Therefore, companies engage independent auditors to examine financial statements to help limit fraudulent activities and build investor confidence in the company's financial reports.

2.3. Artificial neural network

An ANN is a type of artificial intelligence (AI) that employs data mining techniques. ANN must follow established rules, but it generates its own rules based on the examples provided. In other words, this method is trained to perform operations according to sample data (Koskivaara, 2004; Omar et al., 2017). According to Cerullo and Cerullo (1999), an ANN analyzes sample data repeatedly by using patterns, structures, and parallel processing techniques similar to those of the human brain. The advantage of using ANNs is that they provide additional insights into the decision-making process, making ANN one of the valuable methods in finance (Koskivaara, 2004; Omar et al., 2017).

ANN consists of three types of neurons, also known as nodes: 1) input, 2) hidden, and 3) output. Each neuron in ANN is a node, and two nodes are connected by a specific weight that determines the direction of data flow. The input layer, the first layer in a neural network, receives external signals and acts as the independent variable in the analysis. This layer is composed of multiple neurons, each representing one variable. The hidden layer, which is the second layer, transfers signals from the input layer to the output layer without external contact. It can consist of one or more layers, combining all inputs based on weights, performing calculations, and passing the results to the next layer. This hidden layer is also responsible for determining the mapping relationship between inputs and outputs. The output layer is the final layer that transfers data outward as a dependent variable in statistical analysis. It comprises a series of neurons, each representing an output of the network (Chalissa & Suryani, 2024; Uğurlu & Sevim, 2015).

Figure 1. Artificial neural network concept diagram



Source: Chen (2016).

In the ANN model, two types of data can be used. First, training data is used to develop the model during training. In a multilayer perceptron (MLP) ANN, training data helps determine the optimal weights in backpropagation. Second, test data can be used to evaluate the model and estimate the error rate after the final model is selected (Faisal et al., 2019; Nurdini et al., 2018). The backpropagation algorithm is the most frequently used algorithm for the training process (Salehi et al., 2016). A backpropagation network is a type of ANN commonly used for classification or prediction (Wu et al., 2006). Specifically, backpropagation is the algorithm used to train multi-layer perceptrons (MLPs) (Salehi et al., 2016).

2.4. Artificial neural network and fraudulent financial statement

Pressure. In ISA 240, pressure is represented by the threat of bankruptcy, which can be proxied by the solvency ratio (Omar et al., 2017). Wells (1997) states that bankruptcy often occurs due to solvency issues, prompting companies to commit financial statement fraud to prevent investors from withdrawing their funds (Omar et al., 2017). This creates excessive pressure on management to meet third-party demands or expectations (Puspitha & Yasa, 2018). The solvency ratio, also known as the leverage ratio, measures a company's ability to meet its long-term and short-term obligations. A high solvency ratio indicates that a company has a strong capacity to pay its debts but also poses a higher risk of bankruptcy. Conversely, a low solvency ratio is generally safer, as it shows the company has fewer external obligations relative to its assets, thereby enhancing principal confidence and smooth operations. However, low solvency may also suggest an underutilization of debt for growth and limit access to additional funding. In this study, solvency is measured using the debt-to-equity ratio and the total debt-to-total assets ratio to gauge the element of pressure.

Opportunity. In ISA 240, opportunities for fraud can arise from subjective or uncertain financial accounts and inadequate stakeholder oversight. Accounts such as receivables, inventory, sales, gross profit, and total assets are often manipulated and difficult to detect (Omar et al., 2017). An increase in these accounts may indicate poor cash turnover, prompting management to manipulate financial statements to gain principal trust.

Firm size can be used as a proxy for opportunity in detecting financial statement fraud, representing ineffective monitoring (Omar et al., 2017). According to Fama and Jensen (1998), larger firms incur higher agency costs due to increased oversight needs, leading to potential conflicts of interest between management, investors, and creditors. Larger firms are more likely to be scrutinized and detected for income misstatements due to their complex transactions and higher visibility (Dechow et al., 2011). Additionally, they may defer current profits to future periods to avoid new regulations or taxes.

Rationalization. Rationalization is challenging to observe as it involves the state of mind and motivation for committing fraud. ISA 240, rationalization can be measured using profitability ratios to detect aggressive and unrealistic profit trends. Profitability ratios assess a company's ability to generate profit from its total assets (Samsulubis et al., 2019). There is a negative relationship between profitability ratios and financial statement fraud; lower profitability ratios indicate a higher likelihood of fraud (Haqqi et al., 2015). Management might manipulate financial accounts to show higher profitability, attracting investors and preventing bankruptcy, thus preserving the company's reputation (Omar et al., 2017).

3. RESEARCH METHODOLOGY

This research is quantitative and utilizes secondary data in the form of financial reports collected from the OSIRIS database. The population in this study consists of companies listed on Bursa Malaysia, Ho Chi Minh Stock Exchange (HOSE) and Hanoi Stock Exchange (HNX) in Vietnam, IDX, Philippine Stock Exchange (PSE), Singapore Exchange (SGX), and Stock Exchange of Thailand (SET) for the period 2021–2022. The purposive sampling method was applied to select samples based on predetermined criteria. According to these criteria, the samples included in this study are as follows in the table below.

Table 1. Sample criteria

Criteria	*Amount*
Property and real estate companies listed on the stock exchange of ASEAN countries in 2021–2022, taken from the OSIRIS database.	512
The financial data of property and real estate companies in ASEAN countries that are missing or incomplete in the OSIRIS database during the 2021–2022 period.	287
Property and real estate companies in ASEAN countries that are not consecutively listed on the stock exchange of each country during the 2021–2022 period.	55
The number of property and real estate sector companies in ASEAN countries that meet the criteria	170
Total research observations (170 x 2).	340

3.1. Measurement of the key variables

The dependent variable in this study is *financial statement fraud*, which is measured by calculating the F-score model (Naldo & Widuri, 2023). This variable is calculated on a nominal or dummy scale based on the F-score model formula. Dechow et al. (2011) revealed that the F-score has an accuracy level of around 68–70%, depending on the type of fraud that occurs. If a company commits financial statement fraud, the fraud score model value is > 1 (code 1), and companies that are not detected as committing financial statement fraud have a fraud score model value < 1 (code 0).

As for the independent variables, this study uses fraud risk indicators from ISA 240 to represent the fraud triangle factors. The measurements for each independent variable are presented in Table 2.

Table 2. Operational variables

No.	Variable	Fraud risk indicators (ISA 240)	Proxies	Indicator
1	*Pressure*	Threat of bankruptcy	Solvency ratios	Debt / equity
				Total debt / total asset
2	*Opportunity*	Accounts that are difficult to corroborate	Asset turnover ratios	Receivable / sales
				Inventory / sales
				Gross profit / total asset
		Ineffective monitoring by stakeholders	Firm size	Natural logarithm of total assets
3	*Rationalization*	Aggressive or unrealistic profit trend	Profitability ratios	Net profit / total asset
				Net profit / sales
				Sales / total asset
				Working capital / total asset

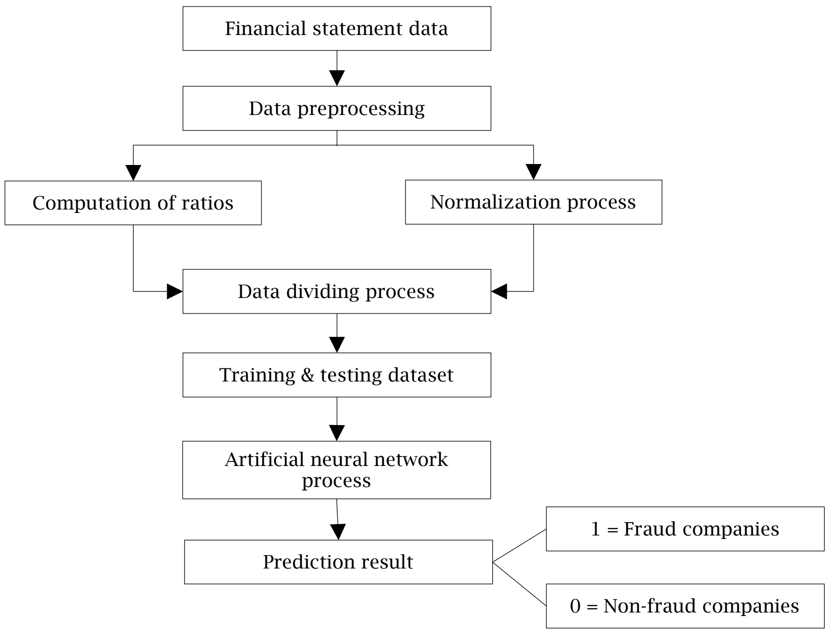
Source: Omar et al. (2017).

3.2. Data analysis

Descriptive statistics will be conducted to summarize the collected data, including the mean, standard deviation, maximum, and minimum values. Additionally, a classification test will be performed to assess the frequency of observed outcomes based on empirical data for the dependent variable.

In this study, the system built to predict financial statement fraud uses an ANN to obtain prediction data. The flowchart can be seen in Figure 2.

Figure 2. Flowchart of the artificial neural network system



Omar et al. (2017) stated in their research that testing using the ANN method involves three parts of the process as follows:

1. *Data normalization.* The data normalization stage is essential for ensuring stability in testing with the ANN method. In this study, as stock exchanges in ASEAN countries do not publish reports on companies involved in fraud, data normalization uses the F-score calculation for property and real estate companies in 2021–2022. The F-score criteria are as follows: 1) if the F-score > 1, the company is classified as fraudulent, and 2) if the F-score < 1, the company is classified as non-fraudulent.

2. *Data set process.* At this stage, for testing the data set process using ANN, the data obtained will be divided into two parts: 1) the training data set and 2) the testing data set. In this study, the data obtained from 2021–2022 amounted to 340 financial reports. The parameters in this study were determined using the trial-and-error method to obtain forecasting results with the highest accuracy.

3. *ANN.* ANN analysis is used to predict the results of dependent variables (output) influenced by independent variables (input).

In testing using ANNs, the independent variable importance test is used to measure the impact of input or independent variables on the prediction results of the ANN (Chen & Du, 2009). To determine which independent variable influences the dependent variable, testing is conducted using SPSS 25.

4. RESEARCH RESULTS

The results of the tests conducted on the sample size in this study can be described in the descriptive statistical test, ANN, and MLP analyses with the following results.

4.1. Descriptive statistical analysis

Descriptive statistical analysis of independent variables that aims to show the minimum, maximum, mean, and standard deviation values of each research variable.

Table 3. Descriptive statistics

Variables	Code	N	Minimum	Maximum	Mean	Std. deviation
Debt equity ratio	*DER*	340	-0.29	2.34	0.1319	0.28442
Leverage ratio	*LEV*	340	0.00	0.66	0.2504	0.16037
Receivable to sales ratio	*RECEIV*	340	0.00	5.19	0.3797	0.76117
Inventory to sales	*INVSAL*	340	0.00	17.54	1.0167	2.02607
Gross profit	*GPM*	340	-0.02	0.56	0.0844	0.06124
Firm size	*LOGTA*	340	7.82	17.20	13.0975	1.72252
Return on assets	*ROA*	340	-0.12	0.43	0.0208	0.04018
Net profit margin	*NPM*	340	-0.78	1.42	0.1098	0.23249
Sales to total assets	*SALTA*	340	0.02	3.13	0.2106	0.25878
Working capital to assets	*WCTA*	340	-0.20	0.81	0.1477	0.20124
Valid N (listwise)		340				

Source: Authors' elaboration using SPSS 25 software.

Based on Table 3, the descriptive statistics for each variable show different values for minimum, maximum, mean, and standard deviation. If the mean value is smaller than the standard deviation, the data is considered heterogeneous (variety), as seen in the variables *DER*, *RECEIV*, *INVSAL*, *ROA*, *SALTA*, *NPM*, and *WCTA*. Conversely, if the mean value is greater than the standard deviation, the data is considered homogeneous (not varied), as in the variables *LEV*, *GPTA*, and *LOGTA.*

Table 4. Descriptive statistics of ASEAN country demographics

Variables	Indonesia	Malaysia	Vietnam	Thailand	Singapore	Philippines
Company	43	61	30	14	15	7
Sample obs.	97	122	60	28	30	14
Financial statement fraud	72	78	46	21	18	12
DER	0.795	0.255	0.1717	0.890	0.0853	0.322
LEV	0.2111	0.2493	0.2186	0.3309	0.3257	0,319
RECEIV	0.2241	0.3485	0.7725	0.1625	0.1840	0.9471
INVSAL	1.2684	0.7322	1.2885	1.7730	0.3172	0.3700
GPM	0.0866	0.0815	0.0836	0.0970	0.0775	0.0843
LOGTA	12.6059	13.0116	12.5680	13.9527	13.9556	15.5514
ROA	0.0222	0.0166	0.0181	0.0333	0.0213	0.0286
NPM	0.1080	0.0934	0.0937	0.1590	0.1206	0.1936
SALTA	0.1964	0.2487	0.1910	0.2037	0.1938	0.1400
WCTA	0.1657	0.1160	0.1797	0.2717	0.0506	0.0250

Source: Authors' elaboration using SPSS 25 software.

Based on Table 4, Malaysia has the highest number of companies committing financial statement fraud among the ASEAN countries studied, followed by Indonesia, Vietnam, Thailand, and the Philippines. These results indicate that financial statement fraud practices are quite significant in the property and real estate sectors in the ASEAN region. The results of the descriptive analysis of financial statement fraud measured using the F-score ratio index can be seen in Table 5 below.

Table 5. Distribution of financial statement fraud samples

		Frequency	Percentage	Valid percentage	Cumulative percentage
Valid	Indications of fraud	245	72.1	72.1	72.1
	No indications of fraud	95	27.9	27.9	100.0
	Total	340	100.0	100.0	

Source: Authors' elaboration using SPSS 25 software.

Table 5 shows that property and real estate companies listed on the ASEAN stock exchange in 2021–2022 had a total sample of 340, with 95 samples not indicating financial statement fraud and 245 samples indicating financial statement fraud. This classification is part of the ANN process known as data normalization.

The second hidden layer generates biases consisting of H(2,1), H(2,2), H(2,3), H(2,4), H(2,5), H(2,6), H(2,7), H(2,8), H(2,9), H(2,10), H(2,11), H(2,12), H(2,13), H(2,14), H(2,15), H(2,16), H(2,17), H(2,18), H(2,19), and H(2,20). The output layer consists of two outputs: 1) financial statement fraud and 2) non-financial statement fraud.

4.2. Artificial neural network analysis

This study uses an MLP network in SPSS 25 to perform data analysis. This network diagram provides several pieces of information, consisting of an input layer, a hidden layer, and an output layer. Figure A.1 (see Appendix) shows the output results of the ANN process with an 80% training and 20% testing sample.

Based on Figure A.1, the input layer includes *DER*, *LEV*, *RECEIV*, *INVSAL*, *GPM*, *LOGTA*, *ROA*, *NPM*, *SALTA*, and *WCTA*. The first hidden layer generates biases consisting of H(1,1), H(1,2), H(1,3), H(1,4), H(1,5), H(1,6), H(1,7), H(1,8), H(1,9), and H(1,10).

4.3. Results of multilayer perceptron

Network testing MLP is a type of ANN where the basic input and output units are organized with neurons in hidden layers. In this MLP testing, the research sample was divided into two parts: 1) 80% for the training sample and 2) 20% for the testing sample.

In the MLP model shown in the table above, it can be seen that the training function only made a prediction error of 22.1%, while the testing function made an error of 18.7%. The presentation can be seen in Table 7.

Table 6. Multilayer perceptron summary

		N	*Percentage*
Sample	Training	265	77.9
	Testing	75	22.1
Valid		340	100.0
Excluded		0	
Total		340	

Source: Authors' elaboration using SPSS 25 software.

Table 7. Multilayer perceptron model summary

Sample	*Observed*	*Result*
Training	Sum of squares error	53.901
	Percent incorrect predictions (%)	30.2
	Stopping rule used	1 consecutive step(s) with no decrease in error[a]
	Training time	0:00:00,06
Testing	Sum of squares error	13.081
	Percent incorrect predictions (%)	18.7

Note: [a] Error computations are based on the testing sample; dependent variable: Y.
Source: Authors' elaboration using SPSS 25 software.

The classification table for predictions using MLP shows the prediction results generated by ANN. In Table 7, the prediction results are classified, where 0 indicates non-fraud and 1 indicates fraud. The accuracy of 81.3% in fraud prediction using ANN can be said to be quite high in the property and real estate sectors in ASEAN. Many studies in this sector show varying accuracy depending on the methods and data used. When compared to similar studies, such as Chen and Du (2009) in detecting financial statement fraud based on Statement of Auditing Standards (SAS) No. 82, the ANN accuracy rate is 92%. For the study of Kasasbeh et al. (2022) on the application of ANN for fraud detection, the use of ANN managed to obtain high accuracy in the various layers used, with 84.76%, 85.13%, and 82.51% in one hidden layer, two hidden layers, and three hidden layers. Suryani and Fajri (2022) showed the results of ANN accuracy in fraud detection of 73.1%. For this reason, ANN with an accuracy of 81.3% is on the upper side of this range, indicating that ANN is an effective and competitive tool for fraud detection. However, there is an error of 18.7% for fraud detection in financial statements, where analysis must be carried out to reduce the risk of false positives and false negatives. The classification table can be seen in Table 8 below.

Table 8. Classification of multilayer perceptron models

Sample	*Observed*	*Predicted*		
		Indication of fraud	*No indication of fraud*	*Percent correct (%)*
Training	Indication of fraud	184	0	100.0
	No indication of fraud	80	1	1.2
	Overall percent (%)	99.6	0.4	69.8
Testing	Indication of fraud	61	0	100.0
	No indication of fraud	14	0	0.0
	Overall percent (%)	100.0	0.0	81.3

Note: Dependent variable: Y.
Source: Authors' elaboration using SPSS 25 software.

Based on Table 8, performance measurement uses a confusion matrix. A confusion matrix is one of the measuring tools used to measure the performance of machine learning models, represented in the form of a matrix. Based on the values in the confusion matrix, the values of accuracy, precision, and recall can be obtained. The accuracy value shows the extent to which the system is able to group data correctly. The precision value is used to see the consistency between the information requested by the user and the answer given by the system. For recall, the level of success of the system in rediscovering information.

Table 9. Standard confusion matrix

Actual class	*Predicted class*	
	True positive (TP)	False negative (FN)
	False positive (FP)	True negative (TN)

Source: Dubey et al. (2020).

Based on the calculations from the confusion matrix as seen in Table 8, the following conclusions can be drawn:

1. *Accuracy*: The accuracy on the testing data (81.3%) is higher than on the training data (69.8%), indicating that the model is not overfitting and its performance improves on the testing data.
2. *Precision*: Precision is very high for both datasets, at 1, meaning that when the model predicts fraud, its prediction is always correct.
3. *Recall*: Recall on the testing data (81.3%) is higher than on the training data (69.8%), indicating that the model is better at detecting fraud cases in the testing data compared to the training data.
4. *Specificity*: Specificity cannot be accurately calculated because TN on the testing data is 0, and FP is also 0, leading to a division by zero.

From this evaluation, the ANN model does not experience overfitting or underfitting. The model shows better performance on the testing data, which might be due to several factors, such as the testing data being easier to predict than the training data.

Table 10. The area under the curve classification

Observed		*Area*
Y	Non-fraud	0.610
	Fraud	0.610

Source: Authors' elaboration using SPSS 25 software.

For this study, based on Figure 5, which was selected randomly, an area under the curve (AUC) value of 0.610 was obtained, indicating that the model has a low classification in distinguishing samples indicated as fraud from non-fraud.

4.4. Independent variable importance

Independent variable importance provides percentage information that shows how important the independent variable is in determining the network. The results of the independent variable importance show how much influence the independent variable has on the dependent variable. Table 10 shows the results of the independent variable importance output in the ANN test using training and testing samples of 80% and 20%.

Table 11. Independent variable importance

Variables	*Importance*	*Normalized importance (%)*
DER	0.105	88.8
LEV	0.086	72.7
RECEIV	0.113	95.7
INVSAL	0.081	68.6
GPM	0.110	93.5
LOGTA	0.103	87.5
ROA	0.102	86.0
NPM	0.093	79.2
SALTA	0.118	100.0
WCTA	0.089	75.4

Source: Authors' elaboration using SPSS 25 software.

From Table 11 above, if the value of normalized importance is > 0.5 (50%), this variable affects financial statement fraud. Vice versa, if the value of normalized importance < 0.5 (50%), this variable does not affect FFS. From Table 11 it can be seen that the variables that influence financial statement fraud include *DER* (88,8%), *LEV* (72,7%), *RECEIV* (95,7%), *INVSAL* (68,6%), *GPM* (93,5%), *LOGTA* (87,5%), *ROA* (86%), *NPM* (79,2%), *SALTA* (100%), and *WCTA* (75,4%).

5. DISCUSSION

Based on Table 11, the results of the normalized importance test show that each risk factor of the fraud triangle has an impact on financial statement fraud.

5.1. The effect of pressure on fraudulent financial statements

Based on Table 11, the results of the normalized importance test show that the pressure proxied by the debt-to-asset ratio and total debt to total assets has a normalized importance value of 88.8% and 72.7%, which is greater than 50%. This means that the *Pressure* variable has a significant influence on *Financial statement fraud* in property and real estate companies listed on the stock exchanges of ASEAN countries in 2021–2022. In this case, management is encouraged to do various things to meet the expectations of the principal, one of which is financial statement fraud. The company's management does not have the ability to repay its debts, so it becomes pressure for management to manipulate (Yesiariani & Rahayu, 2017).

Companies with high leverage levels can face a greater risk of bankruptcy if they are unable to meet their debt obligations. A high debt structure can increase the likelihood of financial statement fraud because the risk shifts from equity holders and managers to debt holders (Spathis, 2002). Chow and Rice's (1982) research shows that with increasing leverage, the potential for wealth transfer from debt holders to managers also increases (Zainudin & Hashim, 2016). This is similar to the research of Putra and Dinarjito (2021), Puspitha and Yasa (2018), Zainudin and Hashim (2016), and Achmad et al. (2022), where the research shows that pressure proxied by the leverage ratio has a significant effect on financial statement fraud.

5.2. The effect of opportunity on fraudulent financial statements

In Table 11, the results of the normalized importance test show that opportunities can be seen from accounts in financial statements that are difficult to prove, such as *RECEIV* (95.7%), *INVSAL* (68.6%), and *GPM* (93.5%), and for ineffective monitoring, which is proxied by company size (*LOGTA*) with a normalized importance value of 87.5% has a normalized importance value greater than 50%. Then the *Opportunity* variable has a significant influence on financial statement fraud in property and real estate companies listed on the stock exchanges of ASEAN countries in 2021–2022. This is in line with research conducted by Faradiza (2018) using the ANN method, stating that opportunity has a significant effect on the occurrence of financial statement fraud.

The opportunity factor represented by accounts that are difficult to detect and company size creates an environment that makes it easier for financial statement fraud to occur because the complexity and subjectivity of the accounts, coupled with a large organizational structure and high transaction volume, increases the opportunity for individuals to commit fraud without being detected. When a company experiences poor or less-than-ideal financial conditions, management tends to manipulate financial statements. Accounts in the asset turnover ratio are accounts that are vulnerable to fraud, such as receivables, inventory, and gross profit. This is because these accounts are often made based on estimates, making it easier for management to manipulate financial statements (Febriani et al., 2022).

5.3. The effect of rationalization on fraudulent financial statements

Based on Table 11, the results of the normalized importance test show that *Rationalization* represented by the profitability ratio to see the aggressive and unrealistic profit trends of companies such as *ROA* (86%), *NPM* (79.2%), *SALTA* (100%), and *WCTA* (75.4%) have normalized importance values greater than 50%, then the *Rationalization* variable has a significant influence on financial statement fraud in property and real estate companies listed on the stock exchanges of ASEAN countries in 2021–2022.

This is in line with research conducted by Somayyeh (2015), which states that profitability has a significant effect on financial statement fraud. The profitability ratio puts pressure and incentives on management to show good financial performance. Pressure to meet shareholder expectations, incentives for performance, the need to obtain favorable credit terms, and compliance with financial agreements all contribute to the tendency to manipulate financial statements. The act of justifying fraud as a necessary or temporary action is often an excuse for management to engage in fraud. Companies with profitability problems tend to have more errors in their financial statements than other companies (Kreutzfeldt & Wallace, 1986). More than half of fraud cases involve revenue manipulation, such as recording revenue prematurely or fictitious revenue (Spathis, 2002; Zainudin & Hashim, 2016).

6. CONCLUSION

The amount of losses due to financial statement fraud has increased in recent years, underscoring the need for a fraud detection model capable of predicting various forms of fraud that may emerge in the future. This study presents a model for predicting and detecting financial statement fraud in the property and real estate sector across ASEAN countries for 2021–2022. Specifically, this study employs ANNs, particularly the MLP, to detect fraud in financial statements using the fraud triangle as a theoretical framework. While the fraud triangle has long been used in various accounting and finance studies, this research extends its application by integrating data mining methods, such as MLP, for predictive analysis, enabling earlier and more accurate detection of potential fraud.

The methodology utilizes financial ratios that represent the components of the fraud triangle to detect financial statement fraud. The results of the model indicate that financial ratios such as *DER, LEV, RECEIV, INVSAL, GPM, LOGTA, ROA, NPM, SALTA*, and *WCTA* are among the most significant variables in detecting financial statement fraud in the property and real estate sector within ASEAN countries. The ANN model achieved an accuracy rate of 81.3%.

The findings have practical implications for stakeholders and company management in preventing financial statement fraud. Property and real estate companies in ASEAN countries should avoid setting overly ambitious profitability targets for long-term goals and instead focus on maintaining financial and operational stability amid ongoing economic uncertainty. Moreover, the presence of financial pressure, as reflected in a high debt-to-equity ratio (88.8%), suggests a financial risk that could trigger financial statement fraud. Companies must manage and avoid excessive reliance on debt to fund property projects that support company operations. Additionally, the opportunity factor, as represented by the ratio of receivables to sales and gross profit, demonstrates high significance in detecting potential fraud. Management should enhance the supervision of receivables and ensure that reported gross profit figures are realistic, thereby increasing investor confidence. The rationalization factor, represented by the ratio of *SALTA* (100%), has the most significant influence on fraud detection, underscoring the importance of regular analysis and comprehensive documentation to prevent fraud.

Practical implications for investors include considering financial factors when assessing the risk of financial statement fraud and utilizing data mining techniques to analyze financial statements. Investors should also conduct thorough due diligence to evaluate the transparency and accountability of management in handling financial statements.

This study also contributes to the fraud triangle theory by demonstrating how data mining techniques, such as ANNs, can enhance the detection of financial statement fraud. By applying ANN in fraud detection, this research provides a fresh perspective on the fraud triangle, which has traditionally relied on qualitative or descriptive methods. Through the use of data mining techniques, we can more precisely assess the relationships between the pressure, opportunity, and rationalization factors in financial reporting, thus opening new avenues for forensic accounting research.

However, this study has several limitations. It is limited to the property and real estate sector in ASEAN countries, meaning the results may not be representative of other industries in the region. Additionally, the study covers only the period from 2021 to 2022, leading to a limited number of observations. The research also relies solely on financial ratios as proxies for the fraud triangle, meaning the results may not be generalizable to other factors in detecting financial statement fraud. The use of only one data mining method also limits the ability to compare these results with those obtained using other techniques. Finally, due to difficulties in obtaining relevant regulations, this study did not incorporate many ASEAN regulations related to financial statement fraud.

For future research, it is recommended to extend the analysis period to five or 10 years to provide a more accurate representation of the phenomenon studied, especially in light of varying market conditions. It is also suggested that future studies explore multiple industries beyond just the property and real estate sector within the context of ASEAN countries. Moreover, including additional measurement proxies for the fraud triangle model or adopting more comprehensive fraud models, such as the fraud pentagon or hexagon, could offer deeper insights into financial statement fraud. Finally, future research should explore other data mining methods, such as decision trees, support vector machines, or random forests, to compare their accuracy and effectiveness in detecting financial statement fraud.

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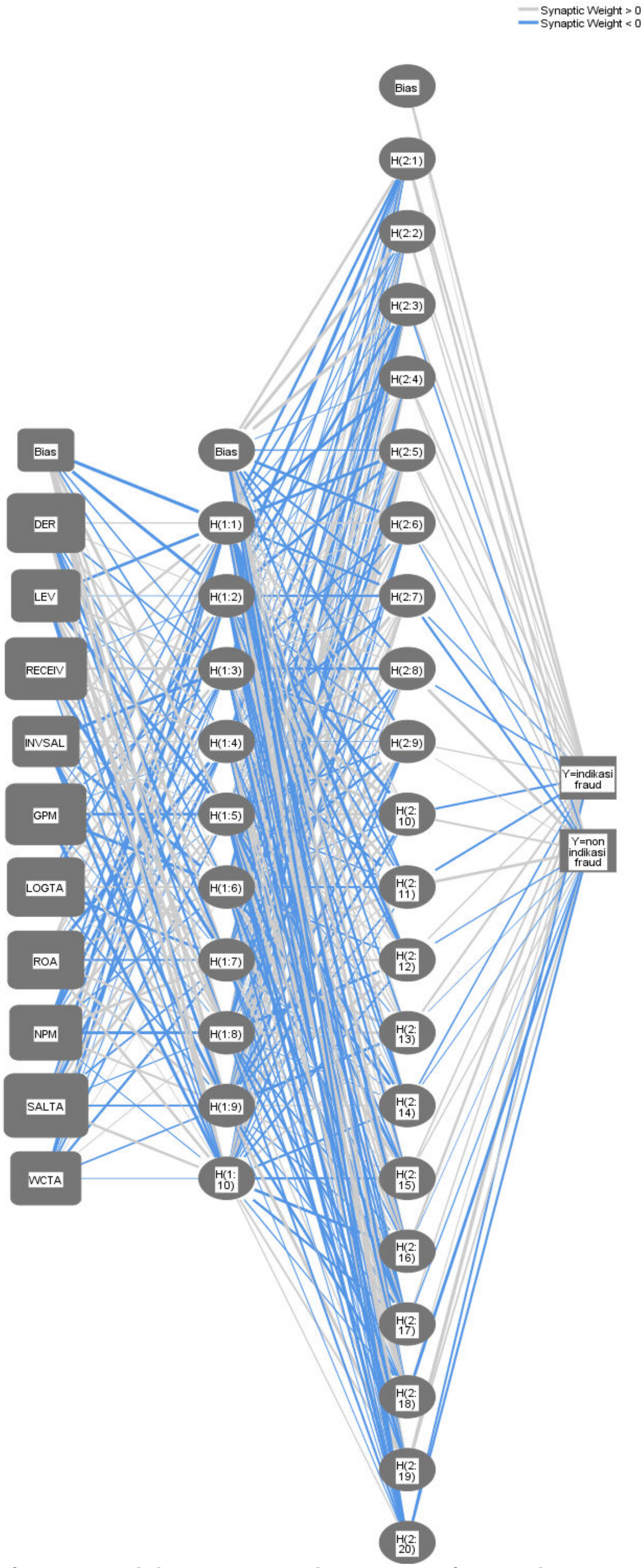
APPENDIX

Figure A.1. Artificial neural network diagram



Note: Hidden layer activation function: Hyperbolic tangent. Output layer activation function: Identity.
Source: Authors' elaboration using SPSS 25 software.