Optimizing to Predict Purchase Intention in Fashion Thrifting Using Artificial Neural Networks Approach

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ABSTRACT

Background : Thrifting has emerged as a prominent trend within the fashion industry, driven by increasing consumer awareness of sustainability and the demand for affordable fashion alternatives

Purpose : This study develops an Artificial Neural Network (ANN) model to optimize purchase intention for thrifting fashion products based on trends, online promotions, and brand image

Methodology : The model uses three node variations (10, 20, 30), two hidden layers, a sigmoid activation function, 10,000 iterations, and a feed-forward propagation algorithm. The 30-node configuration performed best, achieving a determination coefficient of 0.97 during training and 0.98 during testing, indicating high predictive accuracy.

Findings : . The findings confirm that trends, online promotions, and brand image significantly influence purchase intention, demonstrating the model's potential to optimize marketing strategies. By leveraging ANN, businesses can enhance marketing efficiency, adapt to market dynamics, and improve decision-making

Implications : This research highlights the effectiveness of AI-driven methodologies in analyzing consumer behavior and supporting targeted marketing efforts. The model's success also suggests broader AI integration possibilities in strategic planning for the fashion industry

Originality : this study contributes to the literature by providing deeper insights into purchase intention formation and offers practical implications for improving marketing efficiency and strategic decision-making in sustainable fashion businesses

Keywords: *marketing, ANNs, thrifting, Fashion, Artificial Intelligence*

INTRODUCTION

Thrifting has emerged as a prominent trend within the fashion industry, driven by increasing consumer awareness of sustainability and the demand for affordable fashion alternatives (Hasna

Savryaninda & Dias Adiprabowo, 2024; Mim et al., 2024; Primiana et al., 2016). Beyond economic considerations, thrifting is increasingly perceived as a socially responsible consumption practice, aligning with environmental values and the pursuit of unique fashion identities. As this market continues to expand, understanding the determinants of consumer purchase intention in fashion thrifting becomes essential for businesses seeking to design effective and efficient marketing strategies (Dangelico et al., 2022; Singh et al., 2023; Yadav & Sijoria, 2024).

Prior studies indicate that trends, online promotions, and brand image play a critical role in shaping consumer behavior in the fashion sector. Trends influence purchase intention by positioning thrifting as fashionable and ethically desirable (Faerrosa et al., 2024). Online promotions enhance consumer engagement by increasing visibility, accessibility, and interaction through digital platforms (Comilang et al., 2024; Koay et al., 2024). Meanwhile, brand image contributes to trust and credibility, encouraging consumers to associate thrift products with sustainability, authenticity, and value. Despite their relevance, the combined and dynamic effects of these variables on purchase intention in the thrifting context remain insufficiently explored.

From a methodological perspective, analyzing consumer purchase intention involves complex and time-intensive processes due to the subjective and dynamic nature of consumer preferences (Šostar & Ristanović, 2023; Willman-Iivarinen, 2017). Traditional statistical approaches, such as linear regression, factor analysis, and cluster analysis, have been widely applied to examine consumer behavior. While these methods provide valuable baseline insights, they are limited in capturing non-linear relationships and adapting to rapidly changing market conditions (Sarker, 2021; Thiruvengadam et al., 2022) . Consequently, reliance on conventional techniques may result in suboptimal predictive accuracy and limited strategic implications.

To these limitations, Artificial Neural Networks (ANN) offer a robust alternative due to their ability to model complex, non-linear relationships and process large datasets with higher predictive precision (Liyanaarachchi et al., 2021; Prasad & Ghosal, 2022). ANN has demonstrated superior performance in predicting consumer behavior across various domains; however, its application in the context of fashion thrifting, particularly for optimizing purchase intention, remains limited.

Accordingly, this study aims to evaluate the influence of trends, online promotions, and brand image on purchase intention in fashion thrifting by employing an ANN-based approach. The novelty of this research lies in integrating ANN to optimize purchase intention by capturing non-linear consumer behavior patterns within the thrifting market, offering a methodological advancement beyond conventional statistical models. By adopting a consumer-centered and data-driven perspective, this study contributes to the literature by providing deeper insights into purchase intention formation and offers practical implications for improving marketing efficiency and strategic decision-making in sustainable fashion businesses.

METHODOLOGY

This research uses a statistical approach to find solutions to the problems raised. Artificial Neural Networks (ANN) approaches require considerable and reliable data. In addition, this method also require validation of model results. Figure 1 shows the research framework.

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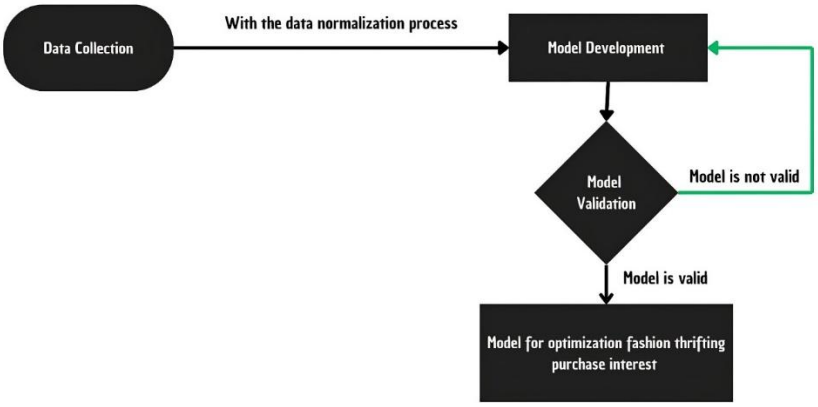


Figure 1. Research Framework

Based on Figure 1, this research has three streams: data collection, modeling, and model validation.

1. Data Collection

Data collection was done secondarily using previous studies that collected relevant information. The data was taken from research by (Astuti, 2023), which collected information aligned with the objectives of this research. A total of 115 respondents participated, comprising 73 males and 42 females. The age distribution showed that 82.1% of the respondents were aged 17–23, while 17.9% were aged 24–30. Regarding occupation, 53.6% were students, 32.1% were employees, and 14.3% were entrepreneurs. The data was collected during February –March 2023, ensuring it reflects current trends and provides a solid basis for analyzing purchase intention in fashion thrifting.

2. Model Development

The model formed in this study consists of three independent variables (X), namely trends, online promotions, and brand image, and one dependent variable (Y), namely purchase intention. Eqs (1-2) show the basic theorem of the Artificial Neural Networks (ANN) model.

$$s_i = \sum\sum w_{ij}x_{ij} + \beta \qquad (1)$$

$$y = ((\varphi(si)+\beta)) \qquad (2)$$

Where s_i is the value of the hidden layer, x_{ij} is the value of the input variable, β is the bias, φ is the activation function, and y is the output variable value. This study utilizes a neural network architecture with two hidden layers, varying the number of nodes at 10, 20, and 30 to identify the optimal configuration for predicting and optimizing consumer interest in thrifting products with the data train is 100. This data for enough to testing understanding model first. The sigmoid activation function was chosen for its effectiveness in capturing non-linear relationships and widespread use in consumer behavior modeling (Liyanaarachchi et al., 2021; Thiruvengadam et al., 2022). It provides a smooth output range between 0 and 1, which aligns with purchase intention analysis. Using two hidden layers balances computational efficiency with the need to model complex variable interactions. The node variations (10, 20, 30) were selected based on literature suggesting that this range is adequate for medium-sized datasets, such as the 115 respondents in this study, offering a balance between model complexity and prediction accuracy (Thiruvengadam et al., 2022). Testing these variations enables the identification of a

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configuration that minimizes error while maximizing performance. A feed-forward propagation algorithm with 10,000 iterations was employed to ensure stable convergence. This detailed consideration of architecture and design choices strengthens the model's reliability and supports its replicability in similar research contexts, addressing the reviewer's methodological rigor and justification concerns.

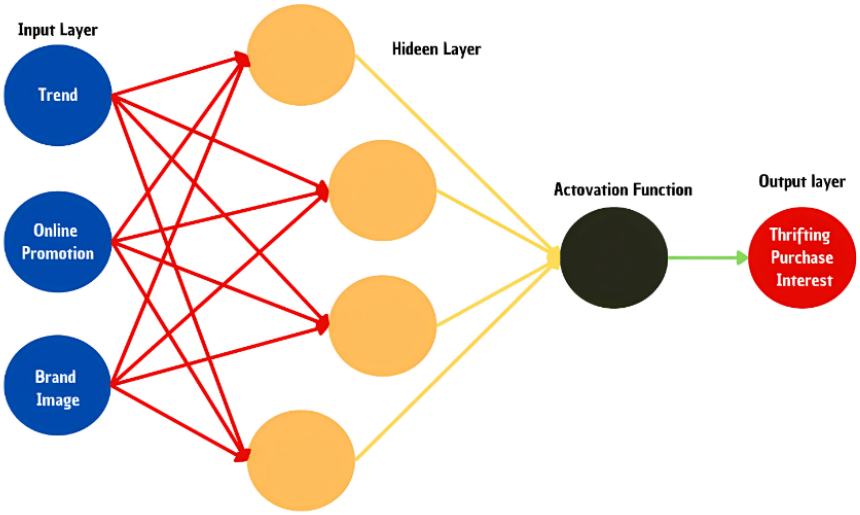


Figure 1. Principles of the architectural model

3. Model Validation

The validation used in this study consists of two stages: validation of model replication with data and validation of the model with further data in the same population. Data validation is performed using the coefficient of determination, which assesses the extent to which the data distribution is similar to the primary data being validated. The range of the coefficient of determination is 0 to 1, where 0 means that the model has no determination at all, and one means that the model has perfect determination. Eq (3) shows the coefficient of determination formula.

$$R^2 = 1 - \frac{RSS}{TSS} \qquad (3)$$

Where RSS represents the residual sum of squares and TSS denotes the total sum of squares. The coefficient of determination is utilized as a validation model because it quantifies how well the independent variables in the model account for variations in the dependent variable.

RESULT AND DISCUSSION

Data Collection

Table 1 outlines the data specifications anticipated by this study, while Table 2 shows the collected data.

Table 1. Data specifications

Variable	Attribute	Function
Trend	Unit	Independent Variable
Online Promotion	Unit	Independent Variable
Brand Image	Unit	Independent Variable

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Thrifting Purchase Interest	Unit	Dependent Variable

Table 2. Result data collecting

No	Trend	Online Promotion	Brand Image	Thrifting Purchase Interest
1	18	16	18	18
2	19	16	19	19
3	20	19	20	20
4	20	20	20	20
5	19	18	18	18
⋮	⋮	⋮	⋮	⋮
115	20	18	19	19

This study astuti (2013) collected 115 data for each variable. The data collected is perspectival, measured on a scale of 1-5, where one indicates that a dependent variable has no influence, and five indicates that it has a very significant influence. These values are the quantitative totals of the perspective assessment results. In this study, 70% of the dataset was used for the training process, while 30% was used for the model validation process. The data sufficiency test shows that the training process can be done with 80 datasets. Eq (4) shows the results of the data sufficiency test.

$$\left[N' = \frac{\frac{k}{s}\sqrt{N(\sum x^2) - (\sum x)^2}}{(\sum x)^2} \right] \qquad (4)$$

Where k represents the confidence level (95%=2), s is the degree of confidence, and x is the observation data. The test data is considered sufficient if N' ≤ N however, if N' > N, the data is deemed insufficient. And the calculation results shows that N' (1.50) < N (80). However, the data above cannot be used to model Artificial Neural Networks (ANNs), as a data normalization process is required first. In this study, data normalization was performed using the Nmax-Nmin method, as shown in Eq (5).

$$X' = \frac{X - Xmin}{Xmax - Xmin} \qquad (5)$$

X' is the normalized data X is the original data, Xmin is the data with the minimum value and Xmax is the data with the maximum value. The results of the data normalization process are shown in Table 3. To gain deeper insights into the data distribution, a thorough visualization of both the original and normalized datasets is conducted. The visualization of the data distribution is presented in Figure 3.

Table 3. Result the normalization

No	Trend	Online Promotion	Brand Image	Thrifting Purchase Interest
1	0.666666667	0.333333333	0.6	0.6
2	0.833333333	0.333333333	0.8	0.8
3	1	0.833333333	1	1
4	1	1	1	1
5	0.833333333	0.666666667	0.6	0.6
⋮	⋮	⋮	⋮	⋮
115	1	0.666666667	0.8	0.8

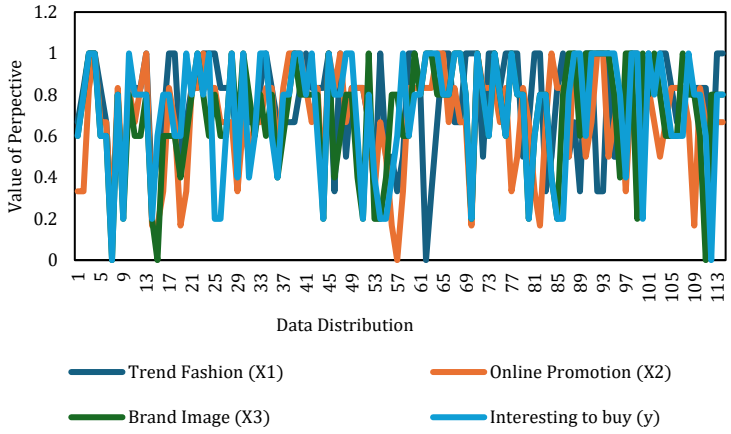


Figure 2. Data Distribution

2. Model Development

Eqs (1) and (2) can be derived into a form that is adjusted to the desired number of nodes. In this research, the variations in the number of nodes used are 10, 20 and 30 nodes with two hidden layer. Eq (6) presents the calculation to calculate the number of weights in the first hidden layer for node variations of 10, 20 and 30.

$$\begin{pmatrix} s_1 \\ \vdots \\ s_{10} \end{pmatrix}_{10x1} = \begin{pmatrix} w_{11} & \cdots \\ \vdots & w_{103} \end{pmatrix}_{10x3} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}_{3x1} \quad (6)$$

$$\begin{pmatrix} s_1 \\ \vdots \\ s_{20} \end{pmatrix}_{20x1} = \begin{pmatrix} w_{11} & \cdots \\ \vdots & w_{203} \end{pmatrix}_{20x3} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}_{3x1} \quad (6)$$

$$\begin{pmatrix} s_1 \\ \vdots \\ s_{30} \end{pmatrix}_{30x1} = \begin{pmatrix} w_{11} & \cdots \\ \vdots & w_{303} \end{pmatrix}_{30x3} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}_{3x1} \quad (6)$$

The total weight in hidden layer one is multiplied by the activation function as in Eq (7).

$$\begin{pmatrix} \Phi_1 \\ \vdots \\ \Phi_{10} \end{pmatrix}_{10x1} = \begin{pmatrix} \varphi(s_1) \\ \vdots \\ \varphi(s_{10}) \end{pmatrix}_{10x1} \quad (7)$$

$$\begin{pmatrix} \Phi_1 \\ \vdots \\ \Phi_{20} \end{pmatrix}_{20x1} = \begin{pmatrix} \varphi(s_1) \\ \vdots \\ \varphi(s_{20}) \end{pmatrix}_{20x1} \quad (7)$$

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$$\begin{pmatrix} \Phi_1 \\ \vdots \\ \Phi_{30} \end{pmatrix}_{30x1} = \begin{pmatrix} \varphi(s_1) \\ \vdots \\ \varphi(s_{30}) \end{pmatrix}_{30x1} \quad (7)$$

Eq (8) shows the inputs for the second layer result calculated in Eq (7), which results in the sum of the weights Ψ_i in the second layer.

$$\Psi_i = \sum\sum {w_{ij}}^{(2)} \varphi(s_i), \quad (8)$$

$$\Psi_i = ({w_{11}}^{(2)} \quad \dots \quad {w_{101}}^{(2)})_{1x10} \begin{pmatrix} \varphi(s_1) \\ \vdots \\ \varphi(s_{10}) \end{pmatrix}_{10x1} \quad (8)$$

$$\Psi_i = ({w_{11}}^{(2)} \quad \dots \quad {w_{201}}^{(2)})_{1x20} \begin{pmatrix} \varphi(s_1) \\ \vdots \\ \varphi(s_{20}) \end{pmatrix}_{30x1} \quad (8)$$

$$\Psi_i = ({w_{11}}^{(2)} \quad \dots \quad {w_{301}}^{(2)})_{1x30} \begin{pmatrix} \varphi(s_1) \\ \vdots \\ \varphi(s_{30}) \end{pmatrix}_{30x1} \quad (8)$$

Neurons transmit the weighted sum of inputs to the activation function, which generates the output. The linear activation function, as outlined in Eq (9) defines the role of the neuron in this process

$$d = ({w_{11}}^{(2)} \quad \dots \quad {w_{101}}^{(2)})_{1x10} \begin{pmatrix} \varphi(s_1) \\ \vdots \\ \varphi(s_{10}) \end{pmatrix}_{10x1} \begin{pmatrix} w_{11} & \dots \\ \vdots & w_{103} \end{pmatrix}_{10x3} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}_{3x1} \quad (9)$$

$$d = ({w_{11}}^{(2)} \quad \dots \quad {w_{201}}^{(2)})_{1x20} \begin{pmatrix} \varphi(s_1) \\ \vdots \\ \varphi(s_{20}) \end{pmatrix}_{20x1} \begin{pmatrix} w_{11} & \dots \\ \vdots & w_{203} \end{pmatrix}_{20x3} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}_{3x1} \quad (9)$$

$$d = ({w_{11}}^{(2)} \quad \dots \quad {w_{301}}^{(2)})_{1x30} \begin{pmatrix} \varphi(s_1) \\ \vdots \\ \varphi(s_{30}) \end{pmatrix}_{30x1} \begin{pmatrix} w_{11} & \dots \\ \vdots & w_{303} \end{pmatrix}_{30x3} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}_{3x1} \quad (9)$$

The above equation is used as a model to find Thrifting Purchase Interest as a trend fashion,online promotion and brand image, as Eq (10) shows.

$$d = (-4.35^{(2)} \quad \dots \quad -14.34^{(2)})_{1x10} \begin{pmatrix} \varphi(s_1) \\ \vdots \\ \varphi(s_{10}) \end{pmatrix}_{10x1} \begin{pmatrix} -7.75 & \dots \\ \vdots & -5.61 \end{pmatrix}_{10x3} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}_{3x1} \quad (10)$$

$$d = (-3.21^{(2)} \quad \dots \quad -3.97^{(2)})_{1x20} \begin{pmatrix} \varphi(s_1) \\ \vdots \\ \varphi(s_{20}) \end{pmatrix}_{20x1} \begin{pmatrix} -2.19 & \dots \\ \vdots & -0.89 \end{pmatrix}_{20x3} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}_{3x1} \quad (10)$$

$$d = (-1.62^{(2)} \quad \dots \quad -2.51^{(2)})_{1x30} \begin{pmatrix} \varphi(s_1) \\ \vdots \\ \varphi(s_{30}) \end{pmatrix}_{30x1} \begin{pmatrix} -1.77 & \dots \\ \vdots & -1.64 \end{pmatrix}_{30x3} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}_{3x1} \quad (10)$$

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To smooth out the noise in the prediction results, a moving average model is used, as shown in Eq (11).

$$\hat{x}_i = \frac{1}{k} \sum_{j=-\frac{k-1}{2}}^{\frac{k-1}{2}} x_i + j, \;\; i = \frac{k+1}{2}, \frac{k+3}{2}, \ldots\ldots, n - \frac{k-1}{2} \tag{11}$$

.

3. Model Validation

1) Replication Test

In this replication test, the iteration results of three node variations in the hidden layer are tested to determine whether the model can replicate the data. The replication test uses the coefficient of determination (R^2). The results of the iteration and replication test can be shown in Table 4 and the distribution is visually displayed in Figure 4.

Table 4. Result model

No	10 nodes	20 nodes	30 nodes	actual
1	0.48	0.50	0.55	0.6
2	0.76	0.77	0.73	0.8
3	0.80	0.81	0.80	1
4	0.77	0.74	0.83	1
5	0.71	0.68	0.60	0.6
⋮	⋮	⋮	⋮	⋮
80	0.54	0.53	0.8	0.8
R^2	0.63	0.79	0.97	-

The model iteration results of the three variations of the number of nodes show that with 1,000 iterations and two hidden layer consisting of 30 nodes, this model has the best coefficient of determination. Visually, the data distribution from the model results with 30 nodes also shows a similar pattern to the actual data. Therefore, based on these results, it is possible to optimize the purchase intention of thrifting fashion products using an ANN model with 30 nodes. However, to build more substantial confidence, it is necessary to test the model with data from different populations. Table 5 and Figure 5 show that the model has had excellent validation in predicting and testing data different from the training data.

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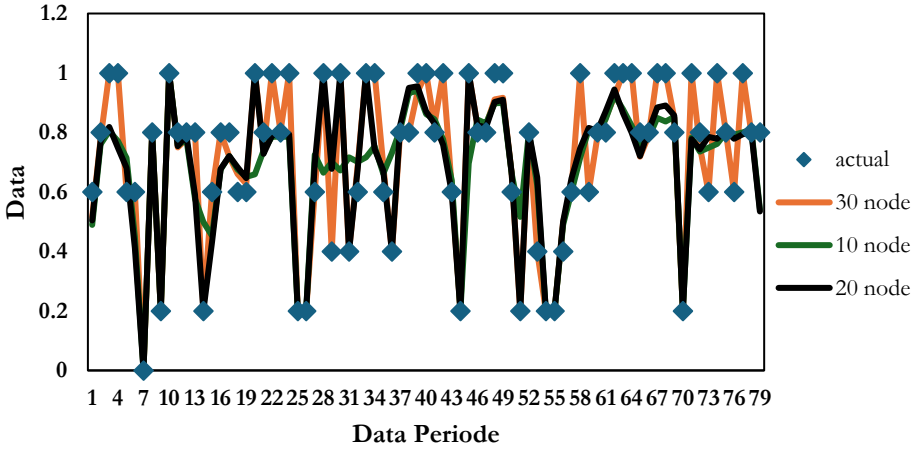


Figure 3. Result model distribution data.

2**) Testing model**

A model test was conducted by comparing the model iteration results with the remaining 35 data sets.

Table 5. Result testing model

No	Model	Actual
1	0.55	0.2
2	0.73	0.6
3	0.80	0.8
4	0.4	0.8
5	0.2	0.4
⋮	⋮	⋮
35	**0.8**	**0.8**
R^2 = 0.98		

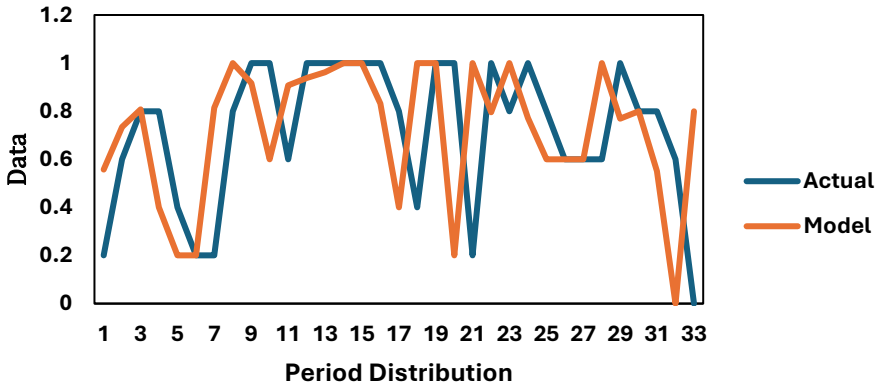


Figure 4. Distribution data

The model testing results show that only 2% of the variance of the actual data cannot be explained by the model. This 2% percentage may be due to the model's limitations in understanding the uncertainty

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of other variables that contribute little. However, this result proves that the purchase intention of thrifting fashion products, which is influenced by trends, online promotions, and brand image, can be approached using an ANN model.

CONCLUSION

This study successfully created an Artificial Neural Network (ANN) model to optimize the purchase intention of thrifting fashion products by examining the impact of trends, online marketing, and brand image. The model performed exceptionally well, with the best results obtained with 30 nodes, two hidden layers, a sigmoid activation function, and 10,000 iterations. The model had a coefficient of determination of 0.97 during training and 0.98 during testing, with only 2% of the data variance remaining unexplained. These findings support the model's capacity to capture non-linear relationships and explain the major aspects that influence purchasing decisions.

The findings of this study highlight the impact of trends, online promotions, and brand image in influencing consumers' purchase intentions for thrifted fashion products. Trends are important because consumers tend to follow the most recent fashion advances, which have emotional and social appeal Astuti (2023). This interest in trends is frequently fueled by the power of social media, influencer recommendations, and fashion community involvement, which promotes the value of exclusivity and self-expression through thrifting products Meanwhile, online advertisements have proven to be a very efficient method for capturing customer attention.

Discounts, flash sales, and the usage of prominent e-commerce platforms are all effective digital marketing methods for increasing consumer involvement and creating a more dynamic shopping experience camillang (2024). On the other side, a strong brand image not only boosts consumer trust but also fosters long-term loyalty. Brands with a good reputation are frequently regarded to have higher product quality, give consumers a sense of security, and elicit powerful emotional responses (Nuseir, et al, 2023). Thus, combining these three criteria might result in an integrated marketing strategy that not only draws customers but also encourages repeat purchases.

However, this study accepts its shortcomings. The model excludes variables such as economic conditions and seasonal trends, which can significantly influence consumer behavior. Economic variations, such as inflation or a recession, can alter buying habits, whilst seasonal trends might influence the appeal of specific products. Future research should take these elements into account in order to improve the model's prediction capacity and gain a better knowledge of the dynamics that drive purchase intention in the fashion thrifting industry. This study offers significant data for industry companies seeking to improve marketing methods, adjust to customer tastes, and achieve a competitive advantage in the fashion thrifting industry.

AUTHOR'S CONTRIBUTION

Fadil Abdullah and Hafiza Aprilia were responsible for the conceptualization of the study. The research methodology, software development, formal analysis, investigation, data curation, visualization, and preparation of the original draft were conducted by Manase. Validation of the research results was carried out collaboratively by Adie Kusna Wibowo, Abdullah, and Fadil. Writing, reviewing, and editing of the manuscript involved Hafiza, while research resources were supported by Fadil.All authors have read and agreed to the published version of the manuscript.

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DECLARATION OF COMPETING INTEREST

The authors declare that they have no competing interests.

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