

## PATH ANALYSIS : DIRECT AND INDIRECT EFFECT HYPOTHESIS TESTING USING JACKKNIFE RESAMPLING ON THE DEVELOPMENT OF A CASHLESS SOCIETY

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### ABSTRACT

*This study investigates the direct and indirect effects of marketing mix variables, namely Product, Price, and Promotion, on the Development of a Cashless Society, with the Digitization of Electronic Money serving as a mediating variable. Path analysis was employed using secondary data obtained from a survey of 100 mobile banking users in Jakarta during the COVID-19 pandemic. To reduce dependence on distributional assumptions, hypothesis testing of the path coefficients was performed using the jackknife resampling method. The results indicate that Price and Promotion have significant positive direct effects on the Digitization of Electronic Money, while the Digitization of Electronic Money has a significant direct effect on the Development of a Cashless Society. Furthermore, Price and Promotion exert significant indirect effects on the development of a cashless society through the mediating role of electronic money digitization, whereas Product has neither a significant direct nor indirect effect. The proposed model achieved a Q-square predictive relevance of 0.5893, indicating moderate-to-high predictive capability. These findings highlight the critical role of electronic money digitization in facilitating the transition toward a cashless society and demonstrate that jackknife resampling provides a robust approach for hypothesis testing in path analysis when normality assumptions are questionable.*

**Keywords:** Path Analysis, Jackknife Resampling, Indirect Effect, Hypothesis Testing

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## INTRODUCTION

Regression analysis can be extended to model systems consisting of multiple structural equations, commonly known as path analysis. One of the distinguishing characteristics of path analysis is that the structural model involves at least one exogenous variable, one intervening endogenous variable, and one pure endogenous variable (Solimun, A. A. R, & Nurjannah, 2017). In this framework, exogenous variables function as predictors that influence other variables, whereas pure endogenous variables only receive the effects of other variables without influencing any subsequent variables. In contrast, intervening endogenous variables simultaneously serve as dependent variables in one structural equation and independent variables in another, allowing them to mediate causal relationships among variables (Krämer, Green, Pollard Jr, & Tugend, 2014).

The inclusion of intervening endogenous variables results in a system of multiple structural equations that cannot be appropriately analyzed using conventional regression techniques. Consequently, path analysis provides an advantage over ordinary regression because it enables researchers to evaluate both direct and indirect effects among variables, whereas regression analysis is limited to estimating only direct relationships (Solimun, 2010). This capability makes path analysis particularly useful for investigating complex causal mechanisms involving mediating variables.

Similar to regression analysis, path analysis requires several statistical assumptions to ensure the validity of parameter estimation and hypothesis testing, one of which is the normality assumption of the residuals. Nevertheless, in this study, hypothesis testing for the path coefficients is conducted using a resampling approach, making the inference less dependent on the normality assumption. According to the Central Limit Postulate, when the resampling procedure is performed using at least 100 observations, the sampling distribution of the estimator tends to approximate a normal distribution. Therefore, increasing the sample size improves the reliability of the statistical inference obtained from the resampling procedure (Solimun, A. A. R, & Nurjannah, 2017).

Path analysis can be applied in various fields, one of which is in banking economics. As in this study, path analysis will be applied to analyze how the mix marketing variables (Product, Price, and Promotion) affect Cashless Society Development. There are three things that affect the marketing of a product or commonly known as the 3Ps, namely Price, Product, Promotion.

Doan et al. (2015) conveyed that product is the first and one of the key marketing elements. Išoraitė (2016) defines Product as everything that can be offered to the market in order to get attention, to be bought, used, or consumed so that the consumer can be satisfied or fulfill consumer needs. The context of the product referred to here is electronic money.

Išoraitė (2016) also stated that one of the most crucial components of the marketing mix is price because it boosts both profits and market share. Price is the total cost to purchase the good (Darmawan & Grenier, 2021). Price is not only one of the most important variables in a competitive environment that directly impacts the sales and profitability metrics of the company, but it's also one of the most adaptable components of the marketing mix that can quickly adjust to changes in the external environment.

Mohammad (2015) & Khan (2014) define promotion as giving a persuasive information to customers about a certain product. Another definition of promotion is a type of marketing communication, which is an information-disseminating marketing activity. Thabit & Raewf (2018) stated developing a product's image within the market is the primary goal of promotion. One of the important competitive tools that can preserve industry vitality is promotion.

Cashless payment system, also referred to as an electronic payment system, usually includes credit cards or digital financial instruments backed by banks or nonbanks. Sellers and buyers can conduct transactions without utilizing physical currency by utilizing cashless payment methods. It is beneficial for businesses to use this payment method since it lowers the cost of financial transactions (Yakean, 2020); (Alzoubi, Alshurideh, Kurdi, & Alhyasa, 2022).

Yakean (2020) stated that the tiny droplets released by talking, sneezing, and coughing can transfer the coronavirus. Since the COVID-19 era, society's customs of conducting business slowly have evolved. People might get infected by COVID-19 by doing transactions using cash or cheque that has been passed from other people. Therefore, during the pandemic, a cashless society was established to reduce physical contact.

Research related to mix marketing variables (product, price, promotion) on the development of cashless society has never been done before. However, there is a similar study and it is still in the same field as research related to cashless society. The previous research has been done by Rumiya & Syafarudin (2021) which the topic of the research is mix marketing on customer satisfaction during the

COVID-19 pandemic. From this study, it was found that the mix marketing variable had an effect on customer satisfaction during the COVID-19 pandemic.

Research related to testing the jackknife resampling hypothesis in the field of health economics is still not widely conducted. Iriany, A., Putri, H. R. A., & Yuwanto, (2022) implemented jackknife resampling for hypothesis testing in path analysis when the normality assumption was violated. Their study demonstrated that jackknife resampling can provide robust standard error estimates and more reliable significance testing for path coefficients. In addition, Papalia et al. (2023) compared Jackknife and Double Jackknife resampling in path analysis and reported that both methods effectively overcome violations of the normality assumption, while Double Jackknife offers higher relative efficiency.

Unlike these previous studies, the present research applies jackknife resampling to examine both the direct and indirect effects of the marketing mix on the development of a cashless society through the digitization of electronic money. Furthermore, this study integrates path analysis with Sobel mediation testing to evaluate the mediating role of electronic money digitization in banking economics. Therefore, the novelty of this research lies not only in the application of jackknife resampling for hypothesis testing under non-normal conditions but also in its application to investigate the mechanisms through which marketing mix variables influence the development of a cashless society.

Based on the explanation above, the topic that would be discussed about is indentifying factors that affect the development of cashless society directly or indirectly titled “Path Analysis: Direct and Indirect Effect Hypothesis Testing Using Jackknife Resampling on the Development of a Cashless Society” which is expected to be used as a reference for the bank in the marketing of e-money products to the public and as a reference for statistical users related to the use of path analysis by taking into direct and indirect effects.

## MATERIALS AND METHODS

The study utilized secondary data derived from a survey conducted among customers of a bank who used mobile banking services in Jakarta during the COVID-19 pandemic in 2021. The survey involved 100 respondents selected as the research sample. The study examined five latent variables, namely Product ( $X_1$ ), Price ( $X_2$ ), Promotion ( $X_3$ ), Digitization of Electronic Money ( $Y_1$ ), and Development of Cashless Society ( $Y_2$ ). Data were collected using a structured questionnaire in which respondents evaluated each statement based on a Likert scale. The conceptual framework illustrating the relationships among the variables investigated in this study is presented in Figure 1.

The reason why researchers are interested in researching these variables is because the development of payment systems has undergone very rapid innovation from year to year as a result of advances in information and communication technology. This transformation encourages a change in people's behavior from the use of cash to a digital payment system (cashless society). The success of this transformation is not only influenced by technological developments, but also by the marketing strategies implemented by financial service providers. Therefore, this study uses the variables Product ( $X_1$ ), Price ( $X_2$ ), and Promotion ( $X_3$ ) as representations of the marketing mix which theoretically plays a role in influencing people's decisions to adopt electronic money. The context of the Product in this study refers to electronic money and the features offered, such as ease of use, transaction security, and completeness of services. Meanwhile, Price reflects the costs that users have to spend in utilizing digital payment services, while Promotion describes various forms of marketing communication that aim to increase public knowledge, trust, and interest in the use of electronic money.

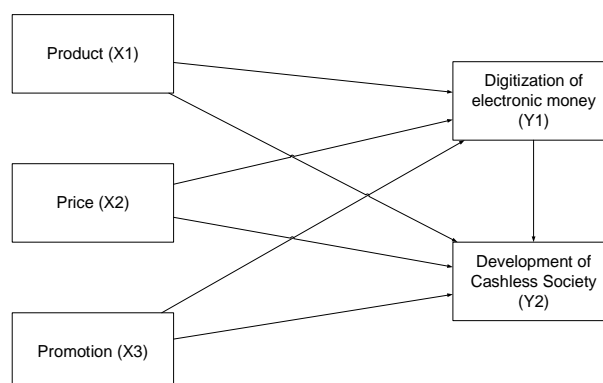


Figure 1. Research Model

The steps of research carried out are as follows.

- 1) Input data from the questionnaire result
- 2) Construct a path diagram based on the structural model design which can be seen in Figure 1.
- 3) Convert a path chart into a system of equations that can be seen in equations (2)
- 4) Testing the linearity assumption using Ramsey’s RESET (Regression Equation Specification Error Test) to determine the form of relationships between variables. If some relationships satisfy the assumption of linearity and others do not, then proceed to the next stage
- 5) Perform path modeling
- 6) Calculates indirect and total influence
- 7) Testing the jackknife resampling hypothesis
- 8) Calculating the value of the coefficient of determination
- 9) Interpret the results of path analysis and influence in the model formed.

**Path Analysis**

The significance of the correlation matrix between two or more causal models that are being compared in the research is assessed using path analysis, an extension of regression analysis. The model is usually figured by a circle-and-arrow figure in which each arrows indicate causal relation (Garson, 2013). Regression equations involving multiple exogenous and endogenous variables can also be tested using path analysis, enabling the testing of intervening or intermediate variables (Cahyoningtyas, Solimun, & Fernandes, 2020). According to Solimun, et al. (2017), The equation model can be written as follows (Solimun, A. A. R, & Nurjannah, 2017).

$$Y_{2n \times 1} = X_{2n \times 9} \beta_{9 \times 1} + e_{2n \times 1} \tag{1}$$

$$\begin{pmatrix} Y_{11} \\ Y_{12} \\ \vdots \\ Y_{1n} \\ Y_{21} \\ Y_{22} \\ \vdots \\ Y_{2n} \end{pmatrix} = \begin{pmatrix} X_{Xn \times 4} & \mathbf{0}_{n \times 5} \\ \mathbf{0}_{n \times 4} & X_{XY} \end{pmatrix} \begin{pmatrix} \beta_{01} \\ \beta_{X_1 Y_1} \\ \beta_{X_2 Y_1} \\ \beta_{X_3 Y_1} \\ \beta_{02} \\ \beta_{X_1 Y_2} \\ \beta_{X_2 Y_2} \\ \beta_{X_3 Y_2} \\ \beta_{Y_1 Y_2} \end{pmatrix} + \begin{pmatrix} e_{11} \\ e_{12} \\ \vdots \\ e_{1n} \\ e_{21} \\ e_{22} \\ \vdots \\ e_{2n} \end{pmatrix}$$

where:

$$X_X = \begin{pmatrix} 1 & X_{11} & X_{21} & X_{31} \\ 1 & X_{12} & X_{22} & X_{32} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & X_{1n} & X_{2n} & X_{3n} \end{pmatrix}$$

$$X_{XY} = \begin{pmatrix} 1 & X_{11} & X_{21} & X_{31} & Y_{11} \\ 1 & X_{12} & X_{22} & X_{32} & Y_{12} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & X_{1n} & X_{2n} & X_{3n} & Y_{1n} \end{pmatrix}$$

Information:

- $Y_{2n \times 1}$  : endogenous latent variable vectors, n: count of observation
- $X_{2n \times 9}$  : the matrix of exogenous latent variable
- $\beta_{9 \times 1}$  : the vector of path coefficients
- $e_{2n \times 1}$  : the vector of inner model’s error

**Path Analysis Assumption**

Solimun, A. A. R, & Nurjannah (2017) explains six assumptions of path analysis, including

- 1) The variables have an additive, linear relationship with one another. A scatter chart can be used to verify the linearity assumption, but the results are not objective. Ramsey originally introduced the Regression Specification Error Test (RESET) in 1969 and it is another technique for confirming the linearity assumption. The general model used to explain the relationship between exogenous and endogenous variables is represented by equation (2).

$$Y_{1i} = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \dots + \beta_p X_{pi} + \varepsilon_{1i} \tag{2}$$

$$Y_{2i} = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \dots + \beta_p X_{pi} + \beta_p Y_{1i} + \varepsilon_{2i}$$

RESET linearity test uses the following hypotheses.

$$H_0: \beta_{p+1} = \beta_{p+2} = \dots = \beta_{p+m}$$

$H_1$ : there is at least one  $\beta_{p+j}$  different from others,  $j = 1, 2, \dots, m$

The following is the procedure for using Ramsey's RESET.

- i) Forming the old regression equation  $Y_i$  of  $X_1, X_2, X_3, \dots, X_p$  so that the estimated value  $\hat{Y}_i$  is 
$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 X_{1i} + \hat{\beta}_2 X_{2i} + \dots + \hat{\beta}_p X_{pi} \tag{3}$$
- ii) Forming the new regression equation  $Y_i^*$  of  $X_1, X_2, X_3, \dots, X_p$  and add exogenous variables which is  $Y_i^2$  so that the estimated value  $\hat{Y}_i^*$  presented in formula (4). 
$$\hat{Y}_i^* = \hat{\beta}_0 + \hat{\beta}_1 X_{1i} + \hat{\beta}_2 X_{2i} + \dots + \hat{\beta}_p X_{pi} + \hat{\beta}_{p+1} Y_i^2 + \hat{\beta}_{p+2} Y_i^3 + \dots + \hat{\beta}_{p+m} Y_i^{m+1} \tag{4}$$
- iii) Calculating the coefficient of determination ( $R^2$ ) from the regression in steps I) and II) which are notated as  $R_{old}^2$  dan  $R_{new}^2$

$$R_{old}^2 = 1 - \frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{\sum_{i=1}^n (Y_i - \bar{y})^2} \tag{5}$$

$$R_{new}^2 = 1 - \frac{\sum_{i=1}^n (Y_i - \hat{Y}_i^*)^2}{\sum_{i=1}^n (Y_i - \bar{y})^2} \tag{6}$$

- iv) From equations (5) and (6), calculate the statistical value of the F test

Rejects  $H_0$  if  $p - value = P(F_{n-p-1-m} \geq F \text{ statistics}) < \alpha$

$$F \text{ statistics} = \frac{(R_{new}^2 - R_{old}^2) / m}{(1 - R_{new}^2) / (n - p - 1 - m)} \sim F_{m, n-p-1-m} \tag{7}$$

Information:

$j = 1, 2, \dots, m$ ,  $m$ : count of additional exogenous latent variable

$p$ : count of previous exogenous variable

$i = 1, 2, 3, \dots, n$ ,  $n$ : count of observation

Based on the hypothesis testing above, if  $p - value < \alpha$ , Then it can be decided that  $H_0$  is rejected so that it can be concluded that the model is not linear.

- 2) The residual is normally distributed. The method for normality testing of residual is Kolmogorov-Smirnov. t-test which can be used to calculate the significance of exogenous variable's impact on endogenous variable, will be valid if the obtained residual from the path model is normally distributed.
- 3) The pattern of relationships between variables is recursive (one-way causal flow system). The characteristics of the recursive model are: a. between  $\varepsilon_i$  is independent. b. Between  $\varepsilon_i$  and  $X_i$  is independent.
- 4) Endogenous variable is at least in an interval measuring scale.
- 5) The variables is measured without mistake (the research instrument must be valid and reliable).
- 6) The specified model under analysis is derived from pertinent theories and concepts.

### Path Analysis Decomposition Model

The decomposition model in path analysis is used to partition the overall relationship among variables into several causal components. This approach enables researchers to distinguish whether the effect of an exogenous variable on an endogenous variable occurs directly or indirectly through one or more mediating variables. In addition, the decomposition model identifies the proportion of the relationship that arises from correlations among exogenous variables rather than from explicit causal pathways. Following Güneri et al. (2017), the decomposition of effects in path analysis consists of the following components.

#### Direct Effect

A direct effect represents the immediate influence of an exogenous variable on an endogenous variable without passing through any intervening variable. It is quantified by the path coefficient

connecting the two variables. For example, the direct effect of  $X_1$  on  $Y_1$  is represented by  $P_{X_1Y_1}$  while the direct effect of  $X_1$  on  $Y_2$  is denoted by  $P_{X_1Y_2}$

#### *Indirect Effect*

An indirect effect occurs when the influence of an exogenous variable on an endogenous variable is transmitted through one or more mediating variables. In this study, the indirect effect of  $X_1$  on  $Y_2$  through the mediator  $Y_1$  is obtained by multiplying the corresponding direct path coefficients. Therefore, the indirect effect is calculated as  $P_{X_1Y_1} \times P_{Y_1Y_2}$

#### *Total Effect*

The total effect represents the overall influence of an exogenous variable on an endogenous variable by combining both direct and indirect effects. Accordingly, the total effect is calculated as  $Total\ Effect = P_{X_1Y_2} + P_{X_1Y_1} \times P_{Y_1Y_2}$ , where  $TE$  denotes the total effect,  $P_{X_1Y_2}$  represents the direct effect, and  $P_{X_1Y_1} \times P_{Y_1Y_2}$  represents the indirect effect through the mediating variable.

#### *Unanalyzed Effect*

An unanalyzed effect refers to the portion of the relationship that arises from correlations among exogenous variables but is not explicitly represented as a causal path in the structural model. Consequently, the association between an exogenous variable and an endogenous variable may be partially explained by its correlation with other exogenous variables included in the model. For example, if  $X_1$  and  $X_2$  are correlated, then part of the relationship between  $X_1$  and  $Y$  may be attributed to the influence of  $X_2$ , even though no direct causal path between these variables is specified.

#### *Spurious Effect*

A spurious effect represents an apparent relationship between two variables that is generated by their simultaneous association with other correlated variables rather than by a genuine causal mechanism. In path analysis, this effect may occur when multiple endogenous variables are influenced by correlated exogenous variables, resulting in an observed association that does not reflect a true direct causal relationship.

### **Ordinary Least Squares (OLS) Estimation**

The path coefficients in this study were estimated using the Ordinary Least Squares (OLS) method. OLS is one of the most widely used parameter estimation methods for linear regression models because it produces estimators that minimize the sum of squared residuals between the observed and predicted values (Gujarati & Porter, 2009). Since path analysis consists of a set of recursive linear structural equations, each structural equation can be estimated separately using the OLS approach. Suppose the structural model is written as

$$Y = X\beta + \varepsilon, \quad (8)$$

where  $Y$  is the response vector,  $X$  is the design matrix containing the explanatory variables,  $\beta$  is the vector of unknown path coefficients, and  $\varepsilon$  is the error vector. The OLS estimator is obtained by minimizing the residual sum of squares (RSS),

$$RSS = (Y - X\beta)'(Y - X\beta). \quad (9)$$

Differentiating the objective function with respect to  $\beta$  and setting the derivative equal to zero yields the normal equations. Consequently, the OLS estimator of the path coefficients is

$$\hat{\beta} = (X'X)^{-1}X'Y \quad (10)$$

The estimated coefficients obtained from OLS represent the direct effects among variables in the path model. These estimates are subsequently used to calculate indirect effects, total effects, and the goodness-of-fit of the model. In this study, the statistical significance of the estimated coefficients was not assessed using the conventional OLS standard errors. Instead, standard errors were estimated using the jackknife resampling method, which provides more robust inference when the normality assumption is questionable

### **Resampling Method**

Resampling techniques are widely employed to evaluate the statistical significance of parameter estimates by repeatedly generating samples from the observed data. In general, resampling is used to estimate sampling variability, standard errors, and confidence intervals without relying heavily on

theoretical distributional assumptions (Efron & Tibshirani, 1994). Because conventional hypothesis testing commonly assumes normally distributed residuals, resampling methods provide an effective alternative when this assumption is violated (Arnastauskaitė, Ruzgas, & Bražėnas, 2021); (Gultom, Solimun, & Nurjannah, 2022). One of resampling methods that can be used is jackknife. In this study, the jackknife resampling technique was adopted to obtain robust standard error estimates for testing the significance of path coefficients.

The jackknife method was originally introduced by Quenouille in 1949 which was used to estimate the bias of an estimator by removing some observations of the sample. The jackknife method is also known as the resampling method without return, so that there is an interlocking relationship in each resampling process. Jackknife resampling is called delete one, which is done by discarding one sample and repeating on each sample until the last. Suppose there is a sample  $x = (x_1, x_2, \dots, x_n)$  and is an estimator  $\hat{\theta} = s(x)$  for a parameter. The steps to estimate the standard error of Jackknife are as follows (Papalia, Solimun, & Nurjannah, 2023).

1. Resampling each Jackknife sample  $x_{(i)} = x_1, x_2, \dots, x_{i-1}, x_{i+1}, \dots, x_n$  where  $i = 1, 2, \dots, n$  by removing one row of data. Suppose there are five samples on variable X, namely:  $x = \{x_1, x_2, x_3, x_4, x_5\}$ . Here is the sampling process in the Jackknife delete-one resampling method:
  - a. First intake  $x_{(1)} = \{x_2, x_3, x_4, x_5\}$
  - b. Second intake  $x_{(2)} = \{x_1, x_3, x_4, x_5\}$
  - c. Third take  $x_{(3)} = \{x_1, x_2, x_4, x_5\}$
  - d. Fourth take  $x_{(4)} = \{x_1, x_2, x_3, x_5\}$
  - e. Fifth intake  $x_{(5)} = \{x_1, x_2, x_3, x_4\}$
2. Calculate jackknife replication for each sample

$$\hat{\beta}_{(i)}^* = s(x_{(i)}^*), b = 1, 2, \dots, n \tag{11}$$

3. Using the standard deviation to estimate the standard error for replicated Jackknife n times.

$$SE_{jack} = \left[ \frac{n-1}{n} \sum (\hat{\beta}_{(i)} - \bar{\beta}_{(.)}^*)^2 \right]^{1/2} \tag{12}$$

with

$$\bar{\beta}_{(.)}^* = \sum_{i=1}^n \frac{\hat{\beta}_{(i)}^*}{n} \tag{13}$$

### Hypothesis Testing of Direct Effect

Solimun et al. (2017) stated that t-test is performed to find out if the endogenous variable is affected by an exogenous variable in a partially significant way. Hypothesis testing of direct effect is carried out using a t-test with the following formula:

$$t - statistics = \frac{\hat{\beta}_j^* - \beta_j}{SE_{\hat{\beta}_j^*}} \sim t_{n-1} \tag{14}$$

Standard errors in t-statistics are obtained from the resampling process using the jackknife method that has been done previously. If  $t_{statistics} \geq critical\ value$  (1.96) so  $H_0$  is rejected. If the test results are significant, it means that exogenous variables significantly affect endogenous variables.

### Hypothesis Testing of Indirect Effect

The indirect effect is estimated using the **product-of-coefficients approach**, commonly referred to as the **Sobel test**. This method evaluates whether the influence of an exogenous variable on an endogenous variable is transmitted through a mediating variable (Abu-Bader & Jones, 2021). According to (Solimun, A. A. R, & Nurjannah, 2017), the Sobel test determines the significance of the indirect effect by combining the estimated direct path coefficients obtained from the path analysis. Statistical significance is assessed using the p-value associated with the calculated z-statistic. If the p-value is less than the predetermined significance level ( $\alpha$ ), the indirect effect is considered statistically significant, indicating that the mediating variable significantly transmits the effect of the exogenous variable to the endogenous variable The indirect effect is calculated as

$$Indirect\ Effect = P_{X1} \times P_{Y1} \tag{15}$$

The corresponding z-statistic is computed using.

$$z_{value} = \frac{(p_1 \times p_2)}{\sqrt{p_1^2 SE_{p_1}^2 + p_2^2 SE_{p_2}^2}} \tag{16}$$

Information:

- $p_1$  : path coefficient of direct effect  $P_{X_1}$
- $p_2$  : path coefficient of direct effect  $P_{Y_1}$
- $p_1 \times p_2$  : path coefficient of indirect effect
- $SE_{p_1}$  : standard error of  $p_1$
- $SE_{p_2}$  : standard error of  $p_2$

**Goodness of Fit**

The goodness of fit of the proposed path model was evaluated using the **Q-square predictive relevance** statistic (Solimun, A. A. R, & Nurjannah, 2017). This statistic measures the predictive capability of the overall structural model by assessing the proportion of variation in the endogenous variables that can be explained by the proposed relationships. In path analysis, a larger Q-square value indicates better predictive performance and greater explanatory power of the model. The Q-square predictive relevance is calculated as

$$Q^2 = 1 - (1 - R_1^2)(1 - R_2^2) \dots (1 - R_p^2) \tag{17}$$

where:

- a.  $R_1^2, R_2^2, \dots, R_p^2$  denote the coefficients of determination ( $R^2$ ) for each endogenous variable in the structural model. The magnitude of each  $R^2$  reflects the explanatory power of the corresponding structural equation and is commonly interpreted as weak, moderate, or substantial.
- b. The Q-square statistic provides an overall measure of the predictive relevance of the path model. Its value ranges from  $0 < Q^2 < 1$ . A value closer to one indicates that the proposed model has stronger predictive capability and explains a greater proportion of the variability in the endogenous variables. Conversely, values approaching zero suggest limited predictive relevance

**RESULTS AND DISCUSSION**

**Result of Linearity Test**

The linearity test is performed using Ramsey's RESET. As for calculating the statistics of the F test in this test, it can be seen in formula (7) which is the ratio of the variety (F statistics) of  $R_{old}^2$  and  $R_{new}^2$ . (equations 5 and 6). Furthermore, after obtaining the statistics of the F test, the p value is sought. The results can be seen in Table 1.

Table 1. Linearity Test Results

Variable	p-value	Result
$X_1 \rightarrow Y_1$	0.6057	Linear
$X_2 \rightarrow Y_1$	0.4780	Linear
$X_3 \rightarrow Y_1$	0.9284	Linear
$X_1 \rightarrow Y_2$	0.6837	Linear
$X_2 \rightarrow Y_2$	0.6951	Linear
$X_3 \rightarrow Y_2$	0.8941	Linear
$Y_1 \rightarrow Y_2$	0.9563	Linear

Table 1, it can be seen that all of these p-values is greater than 0.05 so that  $H_0$  acceptance occurs which indicates that the variables in this study have a linear relationship with one another. Based on the relationship between the variables formed, path analysis can be used.

**Path Estimators and Direct Effect Hypothesis Testing**

The results of the direct effect hypothesis testing are presented in Table 2. The path coefficients were estimated using the Ordinary Least Squares (OLS) method, as described in Equation (10). Statistical significance was evaluated using the t-test with standard errors obtained from the jackknife resampling procedure.

Table 2. Results of testing the hypothesis of direct influence

Variable	Path Coefficient	p-value	Information
$X_1 \rightarrow Y_1$	0.144	0.137	Not Significant
$X_2 \rightarrow Y_1$	0.488	<0.001	Significant
$X_3 \rightarrow Y_1$	0.372	0.001	Significant
$X_1 \rightarrow Y_2$	0.103	0.219	Not Significant
$X_2 \rightarrow Y_2$	0.037	0.393	Not Significant
$X_3 \rightarrow Y_2$	0.098	0.231	Not Significant
$Y_1 \rightarrow Y_2$	0.495	<0.001	Significant

Table 2 shows that four structural relationships are statistically significant at the 5% significance level. Specifically, Price ( $X_2$ ) and Promotion ( $X_3$ ) have significant positive effects on the Digitization of Electronic Money ( $Y_1$ ), with path coefficients of 0.488 ( $p < 0.001$ ) and 0.372 ( $p = 0.001$ ), respectively. In addition, the Digitization of Electronic Money ( $Y_1$ ) has a significant positive effect on the Development of Cashless Society ( $Y_2$ ), with a path coefficient of 0.495 ( $p < 0.001$ ). These findings indicate that improvements in pricing strategies and promotional activities are associated with increased adoption of electronic money, which subsequently contributes to the development of a cashless society. In contrast, Product ( $X_1$ ) does not significantly influence the Digitization of Electronic Money ( $Y_1$ ) ( $\beta = 0.144$ ,  $p = 0.137$ ). Furthermore, none of the marketing mix variables, such as Product ( $X_1$ ), Price ( $X_2$ ), and Promotion ( $X_3$ ), have a statistically significant direct effect on the Development of Cashless Society ( $Y_2$ ), with p-values of 0.219, 0.393, and 0.231, respectively. These results suggest that the marketing mix variables are insufficient to directly encourage the development of a cashless society.

Overall, the findings indicate that the Digitization of Electronic Money ( $Y_1$ ) plays a central role in explaining the transition toward a cashless society. Rather than directly influencing cashless society development, marketing strategies primarily contribute by increasing the adoption and utilization of electronic money, which subsequently promotes cashless payment behavior. Therefore, the digitization of electronic money functions as a key mechanism linking marketing activities to the development of a cashless society.

**Indirect Effect Hypothesis Testing**

The indirect effects were calculated by multiplying the corresponding direct path coefficients, as presented in Equation (15). Specifically, the indirect effect of an exogenous variable on the Development of Cashless Society ( $Y_2$ ) through the Digitization of Electronic Money ( $Y_1$ ) was obtained by multiplying the path coefficient from the exogenous variable to  $Y_1$  by the path coefficient from  $Y_1$  to  $Y_2$ . The statistical significance of each indirect effect was subsequently evaluated using the Sobel test described in Equation (16).

For example, the indirect effect of Price ( $X_2$ ) on the Development of Cashless Society ( $Y_2$ ) was computed as  $0.488 \times 0.495 = 0.242$ , while the indirect effect of Promotion ( $X_3$ ) was calculated as  $0.372 \times 0.495 = 0.184$ . Similarly, the indirect effect of Product ( $X_1$ ) was obtained as  $0.144 \times 0.495 = 0.071$ . The significance of these indirect effects was then assessed using the Sobel test.

Table 3. Results of indirect effect hypothesis testing

Variable	Indirect Effect Value	P-Value	Information
$X_1 \rightarrow Y_2$	0.071	0.227	not significant
$X_2 \rightarrow Y_2$	0.242	0.004	significant
$X_3 \rightarrow Y_2$	0.184	0.024	significant

As shown in Table 3, Price ( $X_2$ ) and Promotion ( $X_3$ ) have significant indirect effects on the Development of Cashless Society ( $Y_2$ ), with indirect effect values of 0.242 ( $p = 0.004$ ) and 0.184 ( $p = 0.024$ ), respectively. These findings indicate that both pricing strategies and promotional activities contribute to the development of a cashless society only through increasing the adoption of electronic money. Since neither variable exhibits a significant direct effect on  $Y_2$ , the influence of Price and Promotion is fully mediated by the Digitization of Electronic Money.

Furthermore, Product ( $X_1$ ) does not have a significant indirect effect on the Development of Cashless Society ( $Y_2$ ) (indirect effect = 0.071,  $p = 0.227$ ). This result suggests that improvements in product features alone are insufficient to increase electronic money adoption to a level that subsequently promotes the development of a cashless society.

Overall, these findings emphasize the important mediating role of the Digitization of Electronic Money. Rather than influencing cashless society development directly, pricing policies and promotional activities first encourage greater utilization of electronic money, which in turn accelerates the transition toward a cashless society. Therefore, electronic money digitization serves as the primary mechanism through which marketing strategies contribute to cashless payment adoption.

### Goodness of Fit

The goodness of fit of the path model was evaluated using the Q-square predictive relevance value, as presented in Equation (17). Since this study involves two endogenous variables, namely Digitization of Electronic Money ( $Y_1$ ) and Development of Cashless Society ( $Y_2$ ), the Q-square value was calculated by combining the  $R^2$  values from both endogenous equations.

$$Q^2 = 1 - (1 - R_1^2)(1 - R_2^2)$$

where  $R_1^2$  is the coefficient of determination for the first endogenous variable ( $Y_1$ ), and  $R_2^2$  is the coefficient of determination for the second endogenous variable ( $Y_2$ ).

Based on the path analysis results, the Q-square value obtained was:

$$Q^2 = 1 - (1 - 0.396)(1 - 0.320)$$

$$Q^2 = 0.5893$$

The obtained Q-square value of 0.5893 indicates that the proposed path model explains approximately 58.93% of the variability in the endogenous variables, while the remaining 41.07% is attributable to factors that are not included in the model. Since the Q-square value is substantially greater than zero and relatively close to one, the model demonstrates moderate-to-high predictive relevance. These results suggest that the proposed model has a satisfactory capability to explain the development of a cashless society through the relationships among Product, Price, Promotion, and the Digitization of Electronic Money, although additional factors beyond the marketing mix may also influence cashless payment adoption.

### CONCLUSION

This study applied path analysis with jackknife resampling to examine the direct and indirect effects of the marketing mix on the development of a cashless society through the digitization of electronic money. The results show that Price and Promotion have significant positive effects on the Digitization of Electronic Money, while only the Digitization of Electronic Money has a significant direct effect on the Development of Cashless Society. Furthermore, Price and Promotion exert significant indirect effects on the development of a cashless society through the mediating role of electronic money digitization, whereas Product shows neither significant direct nor indirect effects. These findings indicate that the adoption of electronic money serves as the primary mechanism through which marketing strategies contribute to the transition toward a cashless society.

From a methodological perspective, the findings demonstrate that jackknife resampling provides a robust approach for hypothesis testing in path analysis by producing reliable standard error estimates without relying heavily on the normality assumption. The proposed model achieved a Q-square predictive relevance of 0.5893, indicating moderate-to-high predictive capability in explaining the development of a cashless society. Practically, financial institutions should prioritize pricing strategies and promotional programs that effectively encourage electronic money adoption. Future studies are recommended to incorporate additional determinants, such as perceived security, trust, financial literacy, technological readiness, and social influence, to improve the explanatory power of the model.

### REFERENCES

- Abu-Bader, S., & Jones, T. (2021). Statistical mediation analysis using the sobel test and hayes SPSS process macro. *International Journal of Quantitative and Qualitative Research Methods*.
- Alzoubi, H., Alshurideh, M., Kurdi, B., & Alhyasa. (2022). The effect of e-payment and online shopping on sales growth: Evidence from banking industry. *International Journal of Data and Network Science*, 6(4), 1369-1380.
- Arnastauskaitė, J., Ruzgas, T., & Bražėnas, M. (2021). An exhaustive power comparison of normality tests. *Mathematics*, 9(7), 1–20.

- Cahyoningtyas, R., Solimun, & Fernandes, A. (2020). The Implementation of First Order and Second Order with Mixed Measurement to Identify Farmers Satisfaction. *Mathematics and Statistics*, 8(6), 671-682.
- Darmawan, D., & Grenier. (2021). Competitive Advantage and Service Marketing Mix. *Journal of Social Science Studies (JOS3)*, 1(2), 75-80.
- Doan, T., Ngo, T., Chiem, T., & Dan. (2015). Analyze The Impact Of Marketing Mix To Brand Image Of A Specific Company (Doctoral dissertation, FUG HCM).
- Efron, B., & Tibshirani, R. (1994). *An Introduction to the Bootstrap*. CRC press.
- Garson, G. D. (2013). *Path analysis*. Asheboro, NC: Statistical Associates Publishing.
- Gultom, F., Solimun, & Nurjannah. (2022). Bootstrap Resampling in Gompertz Growth Model with Levenberg–Marquardt Iteration. *JTAM (Jurnal Teori dan Aplikasi Matematika)*, 6(4), 810-820.
- Güneri, Ö., Göktaş, A., & Kayalı, U. (2017). Path analysis and determining the distribution of indirect effects via simulation. *Journal of Applied Statistics*, 44(7), 1181-1210.
- Iriany, A., Putri, H. R. A., & Yuwanto, A. J. (2022). ESTIMATION OF PATH ANALYSIS WITH JACKKNIFE AND BLINDFOLD RESAMPLING APPROACH. *Journal of Theoretical and Applied Information Technology*, 100(23), 6956–6964.
- Işoraité, M. (2016). Marketing mix theoretical aspects. *International Journal of Research Granthaalayah*, 4(6), 2394-3629.
- Khan, M. T. (2014). The concept of ‘marketing mix’and its elements. *International journal of information, business and management*, 6(2), 95-107.
- Krämer, A., Green, J., Pollard Jr, J., & Tugend. (2014). Causal analysis approaches in ingenuity pathway analysis. *Bioinformatics*, 30(4), 523-530.
- Mohammad, H. I. (2015). 7PS marketing mix and retail bank customer satisfaction in northeast Nigeria. *British journal of marketing studies*, 3(3), 71-88.
- Papalia, M., Solimun, & Nurjannah. (2023). COMPARISON OF RESAMPLING EFFICIENCY LEVELS OF JACKKNIFE AND DOUBLE JACKKNIFE IN PATH ANALYSIS. *BAREKENG: Jurnal Ilmu Matematika dan Terapan*, 17(2), 0807-0818.
- Rumiyati, & Syafarudin, A. (2021). The Influence of Service Quality, Marketing Mix, on Bank Customer. *Iomata International Journal of Tax & Accounting (IJTC)*.
- Solimun. (2010). *Analisis Multivariat Pemodelan Struktural Metode Partial Least Square-PLS*. Malang: CV. Citra.
- Solimun, A. A. R, F., & Nurjannah. (2017). *Metode Statistika Multivariat. Pemodelan Persamaan Struktural (SEM) Pendekatan WarpPLS*. Malang: UB Press.
- Thabit, T., & Raewf, M. (2018). The evaluation of marketing mix elements: A case study. *International Journal of Social Sciences & Educational Studies*, 4(4).
- Yakean, S. (2020). Advantages and Disadvantages of a Cashless System in Thailand during the COVID-19 Pandemic. *The Journal of Asian Finance, Economics and Business (JAFEB)*, 7(12), 385-388.