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Innovation And Branding Strategy Of Local Food MSMES To Increase Competitiveness In Kupang City

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Branding Strategy, E-commerce Adoption; Local Food, MSME Competitiveness; Product Innovation

Abstract
Objective: This study examines how product innovation and branding strategy influence the competitiveness of local food MSMEs in Kupang City, with e-commerce adoption positioned as a mediating variable.
Design/Methods/Approach: A quantitative approach was employed using SEM-PLS based on survey data from 258 local food MSMEs in Kupang City collected through purposive sampling.
Findings: Product innovation and branding strategy have positive and significant direct effects on MSME competitiveness. Branding strategy has a strong and significant effect on e-commerce adoption, while product innovation does not. E-commerce adoption does not significantly affect competitiveness and does not mediate the relationships between innovation/branding and competitiveness.
Originality/Value: This study integrates product innovation, branding strategy, and e-commerce adoption in a single empirical model for local food MSMEs, providing evidence from an underexplored regional context (Kupang City, East Nusa Tenggara).
Practical/Policy implication: MSME development programs should prioritize innovation and branding assistance, while digital interventions should focus on improving digital readiness (skills, logistics, and infrastructure) so e-commerce can contribute effectively.

INTRODUCTION

Local food MSMEs are one of the important pillars in the economy of Kupang City because they contribute to labor absorption, increasing household income, and strengthening regional food security. East Nusa Tenggara (NTT) has abundant local food commodity potential, including corn, soybeans, sorghum, sweet potatoes, beans, and moringa leaves, which have been part of people's consumption patterns as well as a source of livelihood for small business actors (Santoso, 2025; Agriculture and Food Security Service, 2024. However, this potential has not been fully converted into a sustainable competitive advantage because it is still faced with a number of structural and managerial obstacles.

Macro-wise, NTT's economy is still growing relatively moderately, while the agri-food sector is experiencing fluctuating dynamics. The growth of the agricultural sector, which had contracted, illustrates the fragility of the local food production and distribution base, including in Kupang City. At the same time, the increase in local food distribution, including in Kupang City. At the same time, the increase in the price of rice and other food commodities at the national level actually opens up strategic opportunities for strengthening local food as a long-term solution, both for price stabilization and reducing import vulnerability (Boli, 2023; Santoso, 2025). In this context, local food MSMEs in Kupang City have a large room to grow if they are able to optimize innovation and the right marketing strategy.

At the business level, various micro problems still limit the performance of local food MSMEs. Limited production capacity, low packaging quality, lack of product differentiation, and weak understanding of quality standards and food safety make it difficult for local products to compete with similar products from outside the region. Many MSME players still rely on traditional marketing patterns based on conventional markets and local social networks, so their market reach is narrow and vulnerable to changes in demand. This has implications for low competitiveness, limited profit margins, and slow business expansion processes.

As consumer preferences for healthy, sustainable, and locally characterized food products grow, the aspects of innovation and creativity in product development are becoming increasingly crucial. Previous research has shown that the development of innovative forms of local food has great potential to encourage the creation of a creative economy in the food sector (Kijtawee, 2022). Innovation can be carried out through product diversification, increasing added value, modifying recipes, improving packaging, and utilizing simple technology to improve quality. On the other hand, other studies emphasize that creativity and digital strategies are essential to support the preservation and commercialization of local food heritage, especially through strengthening the cultural identity and value inherent in products (Del Soldato & Massari, 2024; Fei et al., 2025).

In addition to product innovation, branding strategy is the main determinant in shaping consumer perception and the bargaining position of MSMEs in the market. Strong branding allows local products to appear with a clear identity, be able to differentiate themselves from competitors, and build an emotional closeness to consumers. Previous research has shown that creative marketing strategies and consistent brand management can increase brand visibility, customer loyalty, and sales performance of food MSMEs (Novie, 2024; Rabasari et al., 2023). However, many MSMEs in Kupang City still view branding as a secondary activity and focus more on the production aspect, so that the potential added value from the brand side has not been utilized optimally.

The development of digital technology and e-commerce platforms actually provides a new channel for MSMEs to expand the market beyond traditional geographical boundaries. Marketing activities through e-commerce can increase access to information, strengthen promotions, and shorten the distribution chain of local products (Szymański, 2021). However, in many regions, including NTT, the use of e-commerce by local food MSMEs still faces various obstacles, including limited digital literacy, uneven internet infrastructure, limited capital for packaging and logistics, and risk perception related to online transactions. As a result, the existence of e-commerce has not automatically contributed significantly to increasing the competitiveness of MSMEs.

From the academic side, a number of studies in Indonesia have examined the creative marketing of MSMEs, the role of tourism in promoting local products, and empowering MSMEs to reduce poverty (Dima et al., 2023; Dima, 2023; Pongge & Dima, 2023). However, most of these studies still focus on general products or examine innovation and branding separately, so there are not many that specifically analyze the simultaneous linkage of product innovation, branding strategies, e-commerce utilization, and the competitiveness of local food MSMEs in one comprehensive empirical model, especially in Kupang City.

Based on these gaps, this study seeks to answer several main questions, namely: 1) How does product innovation affect the competitiveness of local food MSMEs in Kupang City?, 2) How does branding strategy affect the competitiveness of local food MSMEs in Kupang City?, 3) How does product innovation and branding strategy affect the use of e-commerce by local food MSMEs?, 4) Does the use of e-commerce affect the competitiveness of local food MSMEs and play a role in the success of local food MSMEs? as a mediator in the relationship between innovation/branding and competitiveness?

To answer this question, this study uses a quantitative approach using the Structural Equation Modeling–Partial Least Squares (SEM-PLS) method on 258 local food MSME actors in Kupang City. The SEM-PLS model was chosen because it is able to analyze complex causal relationships between latent variables with many indicators and relatively limited sample sizes. The results of the research are expected to provide a theoretical contribution in the form of a more complete understanding of the simultaneous role of innovation, branding, and e-commerce on the competitiveness of MSMEs, as well as provide practical contributions in the form of policy recommendations and strategies for the development of local food MSMEs that are more targeted to local governments, companion institutions, and business actors themselves.

METHODS

This research uses quantitative and qualitative methods. Where this qualitative approach was chosen to obtain a comprehensive overview of the influence of innovation and branding strategies on the competitiveness of local food MSMEs in Kupang City. Quantitative methods were used to test the relationships between variables through Structural Equation Modeling-Partial Least Squares (SEM-PLS) statistical analysis. A qualitative approach is used to deepen understanding of the phenomenon, through in-depth interviews with MSME actors and stakeholders in Kupang City. The respondents of local food MSMEs in this study were 258 people.

The variables used in this study are the competitiveness of local food MSMEs (Y), Product innovation (X1), Branding Strategy (X2), E-commerce (Z). The population in this study is all local food MSME actors in Kupang City, with the following criteria for sample determination: 1) MSMEs engaged in the local food sector (corn, soybeans, sorghum, cassava, sweet potatoes, beans, moringa leaves). 2) Have been operating for at least 2-3 years and above. 3) Have active production and marketing activities. 4) Willing to be a research respondent. The sampling technique used in this study is purposive sampling.

RESULTS AND DISCUSSION

1. Convergent Validity

Convergent validity indicates the extent to which a set of indicators intended to measure a single construct are positively correlated with each other and actually measure the same concept. There are two main criteria for assessing the validity of convergences per construct:

1. **Outer Loadings**

Outer *loadings* are the correlation value between each indicator (question item) and the latent variable (construct) it measures. Functions to assess Convergent Validity and Indicator Reliability. This value indicates how much variance the indicator describes by its latent variable. The higher the value, the better the indicator represents the construct. All indicators that measure reflective latent variables should have *an outer loading* above the set threshold (ideal: 0.70; minimum acceptable limit: 0.50). If there is an indicator that is too low, it means that the question item is invalid in measuring the latent variable in question.

If the Outer Loadings value of ≥ 0.70 is obtained, it can be categorized as very good/ideal. This shows that latent variables explain more than 50% of the variance of the indicator. If the value of Outer Loadings of 0.5-0.70 can be categorized as quite acceptable. This is often tolerated, especially in exploratory research, new scale development, or in social indicator science can be maintained if it does not increase the AVE value. < 0.50 can be categorized as invalid. This indicates that this indicator is weak in measuring constructs and should be considered for removal from the model, especially if removal could increase the value of AVE or Composite Reliability.

Based on the results obtained from the data used, we can conclude that everything escapes the problem with the variance of the indicators used to explain the latent variables. Of the 20 indicators used to explain the latent variable from the variable Product Innovation (IP), it is known that 13 indicators can explain the latent variable very well/ideally, while the other 7 indicators are classified as quite acceptable. For the Branding Strategy (SB) variable, it is known that 16 indicators can explain the latent variables very well/ideally, while the other 4 indicators are classified as quite acceptable. For the E-commerce (EC) variable and the local food MSME (MSME) competitiveness variable, the results were obtained that of the 19 indicators used could explain latent variables very well/ideally, while only 1 other indicator was classified as quite acceptable.

2. Average Variance Extracted (AVE)

AVE is the average of extracted variance or diversity that can be explained by the latent construct (variable) of the indicators (question items) that form it. AVE describes how well these indicators represent the underlying latent variables. The main purpose of AVE is to measure Convergent Validity, i.e. the extent to which a set of indicators that are supposed to measure the same construct, are actually closely correlated with each other. Constructs (variables) are considered to have good Convergent Validity if the AVE value ≥ 0.5. An AVE value of ≥ 0.5 indicates that more than 50% of the variance of the indicator is explained by the construct (variable). This condition must also be supported by a *suggested loading factor* value (correlation between the indicator and the construct) ≥ 0.7 (or at least ≥ 0.5 in certain contexts, especially for exploratory research). Conceptually, the AVE formula for a construct is:

$$AVE = \frac{\sum_{i=1}^{k} \lambda_i^2}{k}$$

Where:

1. λ_i^2 is the *loading factor* (outer weight) of the first indicator in the construct.
2. k is the sum of the indicators for the construct.

Table 1. Average Variance Extracted

Cam	Average variance extracted (AVE)
EC	0.695
IP	0.513
SB	0.575
MSMEs	0.634

Source: Processed Data Results

Based on the results of the data analysis obtained, all constructs have an AVE > 0.50 which indicates that the convergent validity is met. That is, most of the variance of the indicators of each construct is explained by its own construct. In addition, cross-loadings show that the indicators load higher on their original construct than other constructs, thus supporting the validity of the indicator.

3. Heterotrait-Monotrait Ratio (HTMT)

It is a recommended criterion for assessing the validity of discriminators in the analysis of Structural Equation Modeling - Partial Least Squares (SEM-PLS). The goal is to ensure that each reflective construct in the model is completely different from the other. Discriminant validity is achieved if the HTMT value (heterotrait-monotrait correlation ratio) between two reflective constructs is below a certain threshold value. Most researchers, following the advice of Henseler, Ringle, and Sarstedt (2015), recommend an HTMT value of < 0.90 to prove the discriminant validity between two constructs. HTMT was proposed by Henseler et al. (2015) as a more reliable alternative to traditional methods such as the Fornell-Larcker Criterion and Cross-Loadings analysis in the context of PLS-SEM, as older methods proved to be less effective in detecting the lack of discriminant validity in common research situations.

Table 2. Heterotrait-Monotrait Ratio

Construct	EC	IP	SB	MSMEs
EC				
IP	0.532			
SB	0.705	0.835		
MSMEs	0.512	0.786	0.745	

Source: Processed Data Results

Based on the results of the discriminant test above, it can be seen that the HTMT value obtained for all < is 0.90 and even < from 0.85. Based on these results, it can be concluded that the validity of the discriminator has been met. This means that the latent constructs being tested are completely different from each other. Meanwhile, based on the convergent Validity Test conducted from the three validity tests, namely Outer Loadings, Average Variance Extracted (AVE) and Heterotrait-Monotrait Ratio (HTMT), we can conclude that the indicators used to construct variables in this study are really closely correlated and represent the construct or can explain the latent construct (variable) used.

4. Construct Reliability

Reliability refers to the internal consistency of the items that measure a construct. This means that if the measurement is repeated, the results will remain consistent. There are two main metrics for assessing reliability per construct:

1. Composite Reliability (CR)

CR is a measure of internal consistency that measures the extent to which a group of indicators (questionnaire items) that measure the same construct provide consistent results. CR indicates the true reliability level of a construct. The main purpose of Composite Reliability (CR) is to ensure that the latent construct (variable) is reliable or consistent in measuring the phenomenon in question. Conceptually, CR is the ratio between the variance described by the construct (the square of the sum of *the loading factor*) divided by the total measured variance (the described variance plus the error variance).

$$CR = \frac{(\Sigma\lambda_i)^2}{(\Sigma\lambda_i)^2 + \Sigma\left(1 - \lambda_i^2\right)}$$

Where:

1. λ_i is the *loading factor* (outer weight) of the first indicator in the construct.

2. $(1 - \lambda_i^2)$ is the error variance of the first indicator.

If a CR value of ≥ 0.70 is obtained, it can be categorized as good (acceptable). If the CR value of 0.60-0.70 can be categorized as sufficient (acceptable in exploratory research). A < value of 0.60 can be categorized as poor (unreliable).

Table 3. Composite Reliability

Construct	**Composite reliability (rho_a)**	**Composite reliability (rho_c)**
EC	0.979	0.978
IP	0.951	0.954
SB	0.962	0.964
MSMEs	0.971	0.972

Source: Processed Data Results

Based on the results of the analysis, it is known that the CR values obtained from the data used in this study all variables show a CR value of ≥ 0.70, so it can be concluded that all constructs built in this study are classified as good (acceptable) in the model built or show good internal consistency.

3. Cronbach's Alpha (CA)

Cronbach's Alpha (α) is the most commonly used statistical measure to assess the reliability of the internal consistency of a research instrument, such as a questionnaire or scale that uses multiple items to measure a single construct (latent variable). The main purpose of this test is to estimate how strongly the items on the scale are interrelated and measure the same concepts. Cronbach's Alpha values range from 0 to 1. The closer it is to 1, the higher the internal reliability (consistency) of the instrument. Most studies set the cut-off value for Cronbach's Alpha at ≥ 0.70. However, in exploratory research, a ≥ value of 0.60 is sometimes still acceptable. The categories in this CA assessment can be categorized into several categories, including ≥ 0.90 (Very Good), 0.80-0.90 (Good), 0.70-0.80 (Acceptable), 0.60-0.70 (Adequate), < 0.60 (Unreliable)

Table 4. Cronbach's Alpha

Construct	**Cronbach's alpha**
EC	0.977
IP	0.949
SB	0.961
MSMEs	0.969

Source: Processed Data Results

Based on the results of the analysis, the value of internal consistency reliability for all constructs (latent variables) in the model has been tested and considered very good (reliable). Overall, the measurement instruments (questionnaires) used to represent the latent variables in this study had a high level of reliability. This means that respondents provide consistent answers to all questions in a single construct, so that the data collected is reliable and suitable for subsequent structural model testing.

Before entering the Inner model, a multicollinearity test was first carried out. Multicollinearity testing in SEM-PLS is usually performed using VIF (Variance Inflation Factor) on the Inner VIF (for the relationship between constructs) and the Outer VIF (for the relationship between constructs and indicators). Multicollinearity occurs when two or more predictor variables (independent variables) in the model have a very high correlation with each other, thus interfering with the estimation of the path coefficient. In SEM-PLS, although this method is more tolerant of multicollinearity than SEM-CB, testing is still needed to ensure stable estimation results. If the VIF value is < 3.3 → There are no multicollinearity problems (common in SEM-PLS); if you get a score of $3.3 \leq VIF \leq 5$ → Alert, but it can still be accepted in some studies; If a VIF value of > 5 → is obtained A strong indication of multicollinearity, it is necessary to Action; and if a VIF value is obtained > 10 → Serious problem, it is necessary to correct the model.

Table 5. Multicollinearity Test

	VIF
EC ->MSMEs	1.909
IP -> EC	2.773
IP -> MSMEs	2.784
SB -> EC	2.773
SB -> MSMEs	3.849

Source: Processed Data Results

In general, a VIF value below 5 indicates that there is no disruptive multicollinearity in the model. All VIF values in the table are in the range of 1.9 – 3.8, so that:

1. There are no predictor variables that are highly correlated in extreme
2. The structural model used is stable and feasible for the interpretation of the coefficient path
3. The estimation of the regression coefficient between variables is not biased due to collinearity

The highest VIF score is found in the SB → MSME pathway of 3,849, but this value is still below the general threshold (5) so it can still be accepted in SEM-PLS. This value only shows that the contribution of SB to MSMEs has a fairly strong relationship in the model, but has not yet reached the problematic level of multicollinearity. Based on the results of the VIF test, it can be concluded that the SEM-PLS model is free from multicollinearity problems and is suitable to proceed to other stages of internal evaluation of the model (path coefficient, R^2, f^2, Q^2, etc.).

Inner Structural Model Testing (2)

1. Model Predictive Power Test (Model Fit and Relevance)

Once the significance of the relationship is known, we need to assess how well the model built in this study as a whole can explain and predict the data.

1. Coefficient of Determination (R2)

R2 measures the variance in endogenous (dependent) variables that can be explained by exogenous (independent) variables.

Table 6. Coefficient of Determination

Models	**R-square**	**R-square adjusted**
EC (Model 1)	0.476	0.472
MSMEs (Model 2)	0.616	0.612

Source: Processed Data Results

In this study, the adjusted R2 value was used to see the influence of the independent variables used in the study on the dependent variables because it was possible to determine the effect of the addition of independent variables to the model used. Based on the table above, the adjusted R-square value is 0.472 for model 1 which means that E-commerce can be explained by product innovation and branding strategy of 47.2 percent and the remaining 52.8 percent explained by other factors. In model 2, it is known that the adjusted R-square value is 0.612 which means that the competitiveness of local food MSMEs can be explained by E-Commerce, Product Innovation, and Branding Strategy by 61.2 percent and the remaining 38.8 percent by other factors.

2. Predictive Relevance (Q^2)

Q2 is used to assess how well the model is able to predict data outside of the sample used for the estimate.

Table 7. Predictive Relevance

	SSO	**SSE**	**Q^2 (=1-SSE/SSO)**
EC	5140.000	3473.038	0.324

IP	5140.000	5140.000	0.000
SB	5140.000	5140.000	0.000
MSMEs	5140.000	3174.971	0.382

Source: Processed Data Results

E-Commerce Variable (EC)

Q^2 for EC is 0.324 > 0. This means that the model has an adequate predictive relevance to the EC variable. This suggests that the combination of IP and SB is capable of predicting EC values decently, although not entirely dominant.

MSME Variable (MSME Competitiveness)

The Q^2 value for MSMEs is 0.382, which is quite high. This means that the model has good predictive capabilities and is practically relevant in explaining the competitiveness of local food MSMEs. In other words, the combination of IP, SB, and EC makes a strong prediction contribution to MSME variables.
The model has good prediction relevance, especially on the main variable, namely the competitiveness of MSMEs (MSMEs). A Q^2 value above 0.35 (for MSMEs) indicates that the model is suitable for use as a prediction tool in the context of this study. This reinforces R-square's finding that the model not only explains causal relationships but is also adequate in the context of predictive capacity.

3. Impact size test (f^2)

f2 (Effect Size) is used to evaluate the relative impact of each exogenous variable on the endogenous variable in the model. The following are the assessment criteria from the impact test (f2):

Table 8. Impact Size test

Criteria(f2)	**Interpretation (Cohen, 1988)**
F2 > 0.35	Large
F2 > 0.15	Medium
F2 > 0.02	Small
F2 < $0.02	No Effect

Source: Processed Data Results

Table 9. Impact Measurement Test Results

	F-Square
EC -> MSMEs	0.003
IP -> EC	0.004
IP -> MSMEs	0.245
SB -> EC	0.388
SB -> MSMEs	0.054

Source: Processed Data Results

Meanwhile, the results of the impact measure test (f^2) showed that the variable that contributed the most in the model was the Branding Strategy to E-Commerce ($f^2 = 0.388$) which was in the large category. This means that the implementation of branding strategies has a dominant role in encouraging the use of e-commerce by local food MSMEs.

In addition, Product Innovation on MSMEs shows a moderate impact measure ($f^2 = 0.245$), which indicates that product innovation is one of the main determinants in increasing the competitiveness of MSMEs in the market. Meanwhile, the direct influence of branding on the competitiveness of MSMEs ($f^2 = 0.054$) is in the small category, which means that the influence of branding on competitiveness is weaker when compared to its role in e-commerce. In contrast, the influence of E-Commerce on MSMEs ($f^2 = 0.003$) and the influence of Product Innovation on EC ($f^2 = 0.004$) had almost no contribution to the model, suggesting that the two pathways did not provide a meaningful change in explaining the associated endogenous variables.

4. Path Coefficients

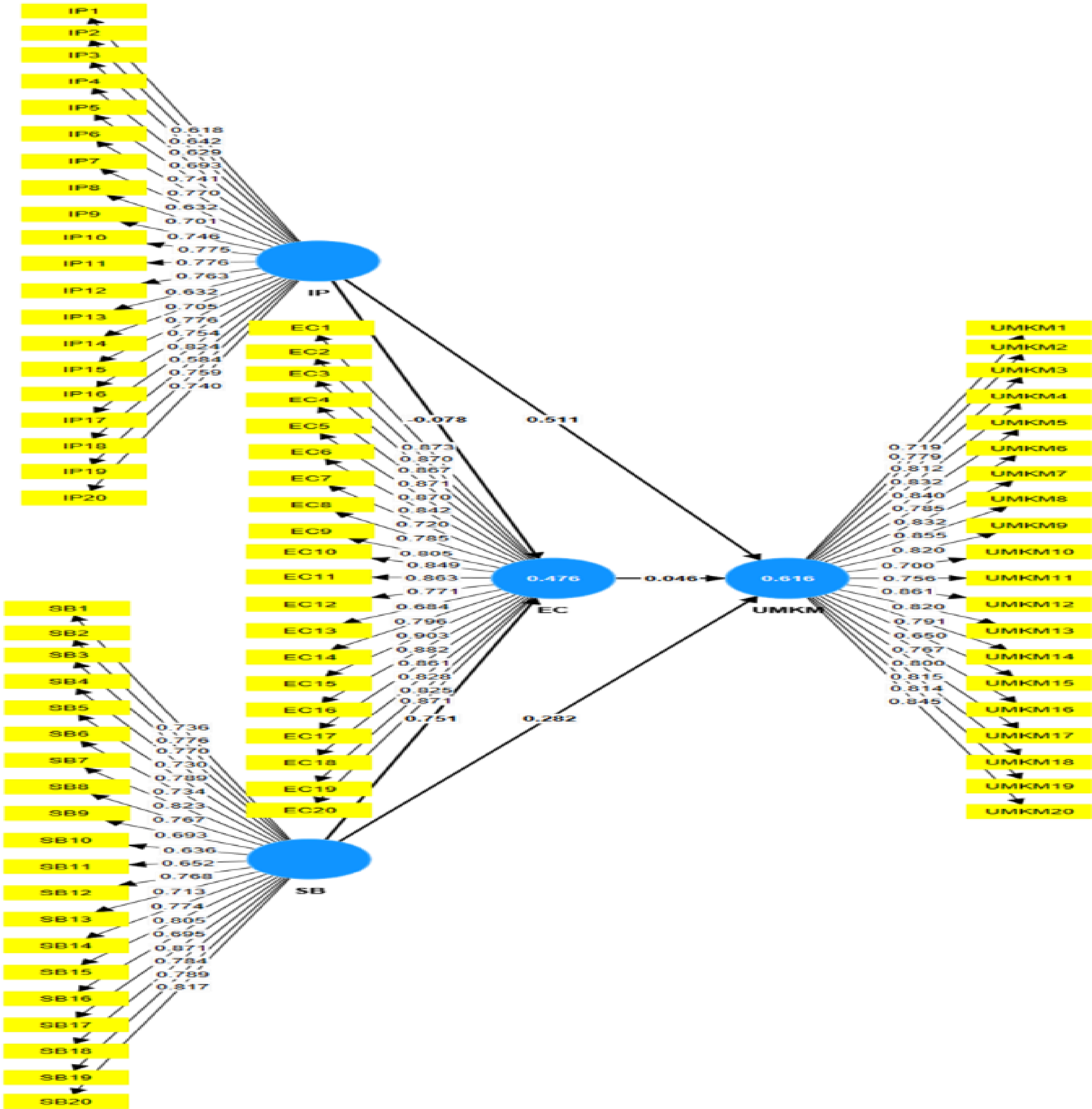

Figure 1. SEM-PLS Model

The significance test of Path Coefficients in SEM-PLS (Structural Equation Modeling - Partial Least Squares) was performed to determine whether the relationship or influence between the hypothesized latent constructs is statistically significant.

To test the significance of Path Coefficients, there are two main criteria that can be used:

Criteria	Formula/ Value	Interpretation (Accepted Hypothesis)
T-Statistics	T-Count > T-Table	Significant relationship (minus H_0).
p-value	p-value < al	Meaningful relationships (minus H_0).

Source: Processed Data Results

In this SEM-PLS analysis, we will look at the direct effects and indirect effects of each variable analyzed in this study.

1. Direct Effects

Table 10. Path Coefficients (Direct effect) results

Direction of Contact	Original sample	Sample mean	Standard deviation	T statistics	P values
EC -> MSMEs	0.046	0.043	0.081	0.561	0.575
IP -> EC	-0.078	-0.081	0.081	0.966	0.334
IP -> MSMEs	0.511	0.517	0.091	5.612	0.000
SB -> EC	0.751	0.755	0.076	9.926	0.000
SB -> MSMEs	0.282	0.280	0.118	2.390	0.017

Source: Processed Data Results

The results of the internal analysis of the model show that some relationships between variables in the model have a significant influence, while others are not statistically significant. The interpretation of each path is explained as follows:

1. The Influence of Product Innovation (IP) on E-Commerce (EC)

The coefficient of IP(X1) → EC (Z) is −0.078 with *a p-value* of 0.334 (> 0.05). Despite the negative coefficient direction, this relationship is not significant. This indicates that product innovations carried out by MSMEs have not been proven to encourage an increase in the use of e-commerce. This can be explained that MSMEs may innovate on products without being followed by digital marketing transformation. This means that product innovation does not automatically make MSME actors more motivated to use e-commerce; Innovation may be more geared towards the needs of offline markets.

2. The Influence of Product Innovation (IP) on the Competitiveness of MSMEs (MSMEs)

The coefficient of IP (X1) → MSMEs (Y) was 0.511 with a *p-value* of 0.000 (<0.05), indicating that the influence was positive and significant. This means that product innovation is a strong factor that increases the competitiveness of local food MSMEs. In the context of local food, innovations in packaging design, flavor variants, health added value, and product differentiation have proven to provide a real advantage in market competition. This is in line with the literature that states that innovation is the key to differentiating MSMEs in competing.

3. The Influence of Branding Strategy (SB) on E-Commerce (EC)

The coefficient of SB(X2) → EC(Z) is 0.751 with *a p-value* of 0.000, which means that this relationship is very significant and strong. This means that the implementation of a good branding strategy (for example, brand identity, storytelling, imagery, and positioning) actually encourages an increase in the use of e-commerce by MSME actors. The better the awareness of MSME actors in building brands, the more likely they are to use digital platforms as marketing channels to strengthen exposure and reputation.

4. The Influence of Branding Strategy (SB) on the Competitiveness of MSMEs (MSMEs)

The coefficient of SB (X2) → MSMEs (Y) is 0.282 with *a p-value* of 0.017 (<0.05). This shows that branding has a positive and significant influence on the competitiveness of local food MSMEs. The success of branding allows MSME products to be more easily recognized, trusted, and positively perceived by consumers, which ultimately strengthens competitiveness in the market.

5. The Influence of E-Commerce (EC) on the Competitiveness of Local Food MSMEs (MSMEs)

The path coefficient of the E-Commerce (Z) → MSME (Y) variable is 0.046 with a *p-value* of 0.575 (>0.05). These results show that the existence or use of e-commerce does not have a significant influence on increasing the competitiveness of local food MSMEs in this study sample. This means that although e-commerce can theoretically expand markets and distribution channels, in the context of local food MSMEs in the region, the use of e-commerce is not strong enough to encourage competitive advantage. This can happen due to several factors, such as low optimization of the use of digital platforms, limited digital capabilities of MSMEs, or markets that are not yet responsive to online-based local products.

Table 11. Indirect effects

Direction of Contact	Original sample	Sample mean	Standard deviation	T statistics	P values
IP -> EC -> MSMEs	-0.004	-0.004	0.010	0.362	0.717
SB -> EC -> MSMEs	0.034	0.033	0.062	0.555	0.579

Source: Processed Data Results

The EC → IP → the direct effect was −0.004 and the P-value was 0.717 (> 0.05).→ This means that the EC does not mediate the relationship between IP and MSMEs, and the direction of the effect is very small (negative but not significant).

SB → EC → UMKMIndirect effect is 0.034 and P-value 0.579 (> 0.05).→ This means that EC also does not mediate the influence of SB on MSMEs. The indirect influence is very small and insignificant.

Based on these two results:

1. No significant indirect effects

2. Thus, the EC variable does not play a mediator in the relationship between IP → MSMEs or SB → MSMEs in this model.

Table 12. Total effect

Direction of Contact	Original sample	Sample mean	Standard deviation	T statistic	P values
EC -> MSMEs	0.046	0.043	0.081	0.561	0.575
IP -> EC	-0.078	-0.081	0.081	0.966	0.334
IP -> MSMEs	0.508	0.513	0.090	5.630	0.000
SB -> EC	0.751	0.755	0.076	9.926	0.000
SB -> MSMEs	0.317	0.313	0.093	3.398	0.001

Source: Processed Data Results

Key Conclusions of Total Effect

1. The IP and SB variables have been proven to have a significant effect on MSMEs.
2. The SB variable also has a strong effect on EC, but IP does not.
3. The EC variable does not significantly affect MSMEs, so its role is weak in this model.
4. This result is also in line with the previous indirect effect results which showed no mediation through EC.

CONCLUSION

This study provides empirical evidence on the determinants of competitiveness among local food MSMEs in Kupang City. The results demonstrate that product innovation plays a critical role in strengthening MSME competitiveness by creating differentiation, enhancing product value, and improving market acceptance. Branding strategy also significantly contributes to competitiveness by strengthening brand identity, consumer trust, and product recognition. In addition, branding strategy has a strong and significant effect on e-commerce adoption, indicating that MSMEs with clearer brand identities are more likely to utilize digital platforms for marketing and promotion.
However, product innovation does not significantly influence e-commerce adoption, suggesting that innovation activities among MSMEs are still largely oriented toward offline markets. Furthermore, e-commerce adoption does not significantly affect MSME competitiveness and does not mediate the relationship between innovation or branding and competitiveness. These findings imply that, in the context of local food MSMEs in Kupang City, digital platforms have not yet become an effective driver of competitive advantage, possibly due to limited digital literacy, infrastructure constraints, and suboptimal utilization of e-commerce features. Overall, the study

concludes that innovation and branding remain the primary strategic levers for enhancing the competitiveness of local food MSMEs, while e-commerce functions more as a complementary tool rather than a decisive competitive factor.

Based on the findings, several recommendations can be proposed. First, MSME development programs should prioritize strengthening product innovation capabilities, including product diversification, quality improvement, and packaging innovation. Second, branding assistance should be intensified through training on brand identity, storytelling, and consistent visual communication to improve market positioning. Third, government and supporting institutions need to focus not only on encouraging e-commerce adoption but also on improving digital readiness, such as digital skills training, logistics support, and infrastructure development, to ensure that e-commerce can effectively contribute to MSME competitiveness.

This study has several limitations. The research focuses on local food MSMEs in Kupang City, which may limit the generalizability of the findings to other regions with different levels of digital infrastructure and market characteristics. In addition, the study uses cross-sectional data, which restricts the ability to capture dynamic changes in innovation, branding, and digital adoption over time. Future research is recommended to employ longitudinal approaches, include additional variables such as digital literacy and logistics capability, and expand the study area to provide a more comprehensive understanding of MSME competitiveness in diverse regional contexts.

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