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Predicting sustainable innovation performance of food MSMEs using SEM-ANN approach

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ABSTRACT

Sustainable innovation performance has become increasingly important for enhancing the competitiveness of micro, small, and medium-sized enterprises (MSMEs), particularly in emerging economies. However, evidence on the influence of strategic orientation dimensions remains mixed, and the moderating role of open innovation is still unclear. In addition, limited research has combined explanatory and predictive approaches to examine both causal relationships and complex patterns. To address these gaps, this study integrates Partial Least Squares Structural Equation Modeling (PLS-SEM) and Artificial Neural Networks (ANN) using data from 183 food-sector MSMEs in Pekanbaru City. PLS-SEM examined causal relationships, whereas ANN captured nonlinear predictive patterns. The findings show that environmental, technological, entrepreneurial, and customer orientations positively influence sustainable innovation performance, with environmental orientation emerging as the strongest predictor, whereas learning orientation exhibits a negative, context-dependent relationship. Open innovation does not significantly moderate these relationships, suggesting that internally aligned strategic capabilities may be more important than external collaboration in resource-constrained settings. This study clarifies the distinct roles of strategic orientation dimensions and the limited moderating role of open innovation in the MSME context. The findings offer practical insights for MSMEs seeking to strengthen innovation performance through strategically aligned internal capabilities.

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INTRODUCTION

Micro, Small, and Medium Enterprises (MSMEs) are vital to Indonesia's economic development, contributing 60,4% of the nation's GDP and employing 97% of the workforce. Despite their significance, they continue to face persistent structural challenges, including limited access to financing, inadequate technological adoption, and restricted market reach, all of which hinder their competitiveness and sustainability. According to Indonesia's Coordinating Ministry for Economic Affairs, barriers in digital transformation and financing further limit their ability to compete globally. As of 2022, only about 17,5 million enterprises had entered the digital ecosystem and leveraged e-commerce, highlighting the need for stronger digital integration efforts (Kementerian Koordinator Bidang Perekonomian 2021). These difficulties are especially pronounced in the agro-industrial sector, where they rely on local agricultural resources but struggle to scale effectively (Dambiski Gomes de Carvalho et al. 2021). Moreover, women-owned enterprises, which account for 42,84% of the total, play a critical role in gender inclusion and socioeconomic empowerment, yet structural limitations continue to pose challenges to their growth (Tambunan 2019).

The COVID-19 pandemic further exacerbated these challenges, severely disrupting supply chains, reducing consumer demand, and restricting business operations, emphasizing the need for strategic solutions. Despite these challenges, the crisis also spurred innovation, prompting many businesses to adopt digital marketing, enhance quality control, and develop consumer-centric products (Tambunan 2020). These adaptive strategies align with growing research that highlights innovation-oriented sustainability as a crucial mechanism for MSMEs to build resilience in volatile environments (Hadjinicolaou et al. 2022, Khomah et al. 2022). Within this context, Strategic Orientation (SO)—an organization's ability to align its strategic direction with dynamic environmental changes and stakeholder expectations (Ruiz-Ortega et al. 2021)—has gained increasing attention as a key determinant of their sustainability (Hall et al. 2022).

Extensive research has examined the role of Strategic Orientation (SO) in enhancing organizational performance, particularly in fostering creativity, knowledge-sharing, and social networking within Industry 4.0 (Muafi 2020). However, most studies rely on Structural Equation Modeling (SEM), which has limitations in capturing complex, non-linear relationships among business variables (Hair, Jr. et al. 2022). To address this, Artificial Neural Networks (ANNs), inspired by the human brain, have been introduced as computational models that process information through interconnected neurons and weighted connections, enabling them to capture complex patterns and improve predictive performance (Kim et al., 2016). Therefore, ANN is employed to complement SEM by providing predictive insights into relationships that are not fully captured through linear modeling. While ANN has been applied to assess SO in the context of economic sustainability (Yang et al. 2022), few studies have explored its integration with Open Innovation (OI) as a moderating factor.

Open innovation refers to the process of leveraging external and internal knowledge flows to enhance innovation outcomes (Bogers et al., 2019). Prior research has predominantly examined OI as a mediator, explaining how external collaboration influences innovation performance (Roh et al. 2021). However, its role as a moderator, specifically in altering the strength of the relationship between SO and Sustainable Innovation Performance (SIP), remains underexplored.

In this study, sustainable innovation performance reflects a firm's ability to generate innovation outcomes that simultaneously create economic, environmental, and social value (Zhang and Chen 2022). Unlike mediation, which explains the mechanism through which variables influence outcomes, moderation captures how the strength of relationships changes under different conditions. Therefore, examining OI as a moderator provides a more nuanced understanding of contextual effects in MSMEs.

Given these gaps, further research is needed to analyze how SO influences SIP, especially considering OI as a potential moderator. Although SEM-based studies suggest innovation capacity can partially moderate SO's impact on MSME performance (Bekata and Kero 2024), they do not account for non-linear dynamics, which may limit their predictive capability. Additionally, while hybrid models such as PLS-SEM combined with ANN have demonstrated improved predictive performance (Devianto et al. 2023), their application in sustainability-focused MSME research remains limited.

To address these limitations, this study proposes an integrated ANN-PLS-SEM framework to examine the non-linear interactions between SO and SIP while incorporating OI as a moderating factor. By combining causal explanation and predictive modeling, this approach provides a more comprehensive understanding of both linear and nonlinear relationships. The findings contribute to both academic literature and practical policymaking by offering insights to help MSME stakeholders integrate strategic orientation with sustainable innovation strategies and enhance competitiveness in dynamic markets.

METHOD

Research Framework

This study develops a conceptual framework to examine how strategic orientation (SO) influences sustainable innovation performance (SIP) in MSMEs, with open innovation (OI) as a moderating variable. Strategic orientation is reflected in five dimensions—environmental, technological, entrepreneurial, learning, and customer orientation—which capture key strategic orientations that shape firms' innovation behavior. Accordingly, it is hypothesized that each dimension of strategic orientation positively influences sustainable innovation performance, while open innovation moderates these relationships.

Each dimension contributes differently to innovation performance. Environmental orientation contributes to green innovation and long-term competitiveness through ecological practices and resource efficiency (Zameer et al. 2022, Aftab et al. 2024), while technological orientation supports innovation capability through the adoption of advanced technologies (Chaparro-Banegas et al. 2024, Jaradat et al. 2024). Entrepreneurial orientation enables firms to act proactively and respond to market changes (Amankwah-Amoah et al. 2019, Diabate et al. 2019), and learning orientation strengthens knowledge development and adaptive capability (Wahyuni and Giantari 2019, Marrucci and Rialti 2024). Customer orientation further ensures that innovation remains aligned with market needs and enhances firm performance (Na et al. 2019, Ulvenblad et al. 2019).

Open innovation further shapes how these orientations translate into innovation performance by enabling firms to leverage external knowledge and collaboration (Parida et al. 2012, Bagherzadeh et al. 2020). Its effectiveness, however, depends on how firms manage external knowledge flows (Barge-Gil 2013). The Structural Equation Modeling (SEM) framework (Figure 1) outlines the conceptual model.

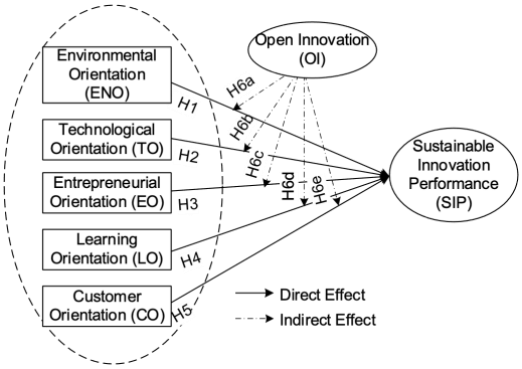

Figure 1 Research hypotheses

Research Stages

This studyadopts a sequential approach that integrates explanatory and predictive analyses,as depicted in Figure 2. The process begins with identifying the research problem and collecting data from food MSMEs using a structured questionnaire. The data are first analyzed using PLS-SEM to evaluate the measurement and structural models, ensuring that the constructs are reliable and theoretically grounded. Latent variable scores obtained from this stage are then used to form a dataset for the next phase of analysis.

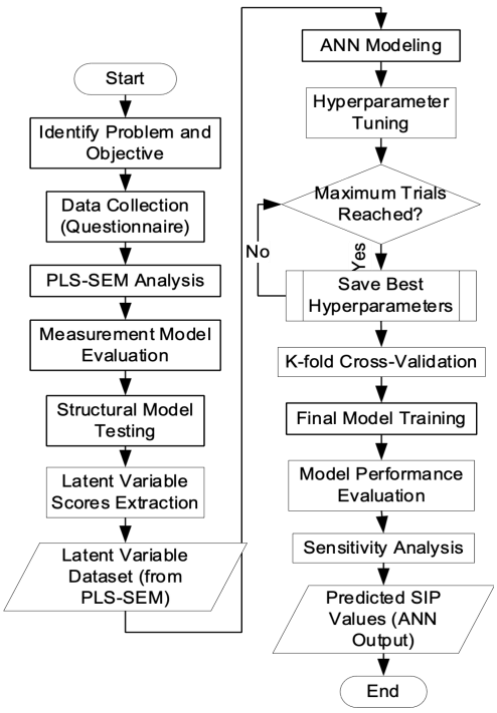

Figure 2 Research stages

In the predictive stage, an Artificial Neural Network (ANN) model is developed using these latent variables as inputs to predict sustainable innovation performance (SIP). The model undergoes hyperparameter tuning through iterative trials to determine the optimal configuration, followed by K-fold cross-validation to ensure robustness. The final model is then trained and evaluated using standard performance metrics, and a sensitivity analysis is conducted to assess the relative importance of each input variable.

Data Collection

This study was conducted in Pekanbaru City, focusing on food-sector MSMEs. Data were collected using a structured questionnaire designed to measure strategic orientation, sustainable innovation performance, and open innovation. A non-probability sampling approach with convenience sampling was employed, considering criteria such as business size and industry relevance. The sample size was determined using G*Power analysis, resulting in a minimum requirement, while the final sample consisted of 183 MSMEs. A pretest was conducted prior to full-scale data collection to ensure the validity and reliability of the instrument.

Measurement of Variables

Data were collected using a five-point Likert scale ranging from "strongly disagree" (1) to "strongly agree" (5). All constructs were modeled as reflective first-order constructs. Strategic orientation was measured using five dimensions: environmental orientation (Zhang and Walton 2017), technological orientation (Hakala and Kohtamäki 2011), entrepreneurial orientation (Jantunen et al. 2008), learning orientation (Nguli 2020), and customer orientation (Deshpandé and Farley 1998). Sustainable innovation performance was measured based on H. Zhang & Chen, (2022), while open innovation was measured following Roh et al. (2021). To improve data quality, procedures such as clear instructions, respondent anonymity, and randomized item ordering were applied.

PLS-SEM Analysis

The analysis was conducted in two stages, beginning with PLS-SEM using SmartPLS 4 Professional (Ringle et al. 2024) to assess both the measurement and structural models. The measurement model was evaluated in terms of indicator reliability, internal consistency (Cronbach's alpha and composite reliability), convergent validity (AVE), and discriminant validity (HTMT), following established guidelines (Hair, Jr. et al. 2022). The structural model was then examined using variance inflation factor (VIF), path coefficients, coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2). In addition, predictive performance was assessed using PLS-Predict and CVPAT. Following this, a two-stage PLS-SEM approach was applied, in which latent variable scores were extracted and used as inputs for the subsequent nonlinear analysis (Hair Jr et al. 2023).

ANN Analysis

In the second stage, an Artificial Neural Network (ANN) model was developed to capture complex patterns and enhance predictive performance. Latent variable scores obtained from PLS-SEM were used as input variables, while sustainable innovation performance (SIP) was treated as the target variable. The model was implemented in Python (Google Colab) and optimized using Keras Tuner with Bayesian Optimization, with up to 100 trials conducted to identify the optimal configuration. Model validation was performed using K-fold cross-validation (K = 5), and performance was evaluated using MSE, RMSE, MAE, and R^2. A sensitivity analysis based on the perturbation method was conducted to assess the relative importance of input variables (Khan et al. 2023). As ANN focuses on prediction rather than causal interpretation, its results complement the explanatory findings obtained from PLS-SEM.

RESULTS AND DISCUSSIONS

Demographic Descriptive

The demographic profile of respondents is presented in Table 1. The sample is predominantly female, accounting for the majority of MSME actors in the food sector. Most businesses have been operating for 5–10 years, followed by those with more than 10 years of experience, indicating a relatively established business landscape. In terms of firm size, the vast majority of MSMEs operate on a micro scale, employing fewer than five workers. This distribution reflects the dominance of micro enterprises within the food MSME sector in Pekanbaru.

Constructs Reliability and Validity

The measurement model demonstrates satisfactory reliability and validity, as presented in Table 2. All indicator loadings exceed the recommended threshold of 0,70, indicating

adequate indicator reliability. Internal consistency is also confirmed, with Cronbach's alpha and composite reliability values above the 0,70 threshold across all constructs. Among the constructs, open innovation exhibits the highest level of internal consistency, while learning orientation shows comparatively lower but still acceptable reliability. Convergent validity is established, as all constructs report AVE values above the 0,50 threshold, indicating that the indicators adequately capture the underlying constructs. Overall, these results confirm that the measurement model is sufficiently robust to support further structural analysis.

Table 1 Respondent descriptive

Characteristic	Group	Frequency	%
Gender	Female	131	71,58
	Male	52	28,42
Firms age	<5	22	12,02
	5 – 10	97	53,01
	>10	64	34,97
Total Workforce (Person)	1 – 4	179	97,81
	5 – 19	4	2,19

Table 2 Constructs' reliability and validity

Latent Variable	Manifest Variable	Loading Factor	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average Variance Extracted (AVE)
CO	CO10	0,775	0,781	0,790	0,858	0,602
	CO6	0,757				
	CO7	0,833				
	CO9	0,735				
ENO	ENO1	0,888	0,883	0,926	0,915	0,731
	ENO2	0,775				
	ENO3	0,919				
	ENO4	0,831				
EO	EO3	0,792	0,856	0,865	0,896	0,634
	EO4	0,815				
	EO6	0,809				
	EO7	0,836				
	EO9	0,727				
LO	LO2	0,705	0,702	0,701	0,815	0,525
	LO6	0,753				
	LO7	0,728				
	LO9	0,710				
OI	OI1	0,886	0,936	0,945	0,951	0,796
	OI2	0,897				
	OI3	0,907				
	OI4	0,937				
	OI5	0,830				
SIP	SIP1	0,785	0,881	0,892	0,909	0,626
	SIP2	0,805				
	SIP3	0,722				
	SIP4	0,788				
	SIP5	0,866				
	SIP6	0,775				
TO	TO2	0,864	0,870	0,878	0,911	0,719
	TO3	0,786				
	TO4	0,871				
	TO5	0,869				

Table 3 Discriminant validity

HTMT	CO	ENO	EO	LO	OI	SIP	TO	OI x ENO	OI x LO	OI x TO	OI x EO
CO											
ENO	0,480										
EO	0,896	0,530									
LO	0,866	0,755	0,895								
OI	0,655	0,297	0,645	0,472							
SIP	0,855	0,658	0,848	0,732	0,672						
TO	0,868	0,302	0,881	0,654	0,663	0,792					
OI x ENO	0,132	0,338	0,168	0,311	0,051	0,134	0,097				
OI x LO	0,073	0,292	0,110	0,323	0,239	0,153	0,129	0,495			
OI x TO	0,079	0,124	0,095	0,102	0,261	0,108	0,049	0,195	0,535		
OI x EO	0,098	0,179	0,162	0,156	0,359	0,139	0,038	0,436	0,594	0,519	
OI x CO	0,078	0,129	0,099	0,166	0,266	0,047	0,049	0,012	0,283	0,597	0,583

Table 4 Hypothesis test results

	Path	Path Coefficient	Inference
H5	CO -> SIP	0,229***	Supported
H1	ENO -> SIP	0,463*	Supported
H3	EO -> SIP	0,145*	Supported
H4	LO -> SIP	-0,143***	Rejected
H2	TO -> SIP	0,273***	Supported
H6a	OI x ENO -> SIP	0,014	Rejected
H6d	OI x LO -> SIP	0,061	Rejected
H6e	OI x CO -> SIP	-0,057	Rejected
H6c	OI x EO -> SIP	0,065	Rejected
H6b	OI x TO -> SIP	0,004	Rejected

* (significant at 0,05) *** (significant at 0,001)

Discriminant Validity

Discriminant validity was assessed using the HTMT criterion, as shown in Table 3. All HTMT values fall below the recommended threshold of 0,90, supporting the discriminant validity of the constructs. Although several construct pairs—such as customer orientation and entrepreneurial orientation, as well as learning orientation and entrepreneurial orientation—approach the upper threshold, these values remain within acceptable limits. This suggests that while the constructs are conceptually related, they remain empirically distinguishable within the model. Taken together, the results indicate that the measurement model achieves adequate discriminant validity

Structural Model Results

The structural model results are presented in Table 4 and were obtained using PLS-SEM with bootstrapping procedures in SmartPLS to estimate path coefficients and assess their significance at a 95% confidence level. Environmental, technological, entrepreneurial, and customer orientations are found to have positive and significant effects on sustainable innovation performance (SIP), supporting the proposed hypotheses. Among these, environmental orientation emerges as the most influential factor, underscoring its key role in driving sustainable innovation within MSMEs.

In contrast, learning orientation shows a significant negative effect on SIP, indicating a direction opposite to the hypothesized relationship. This suggests that, rather than enhancing innovation performance, learning-related practices may not always produce the expected outcomes, particularly when they are not effectively aligned with organizational needs or capabilities. Furthermore, the moderating effects of open innovation are not significant across all relationships. This finding implies that open innovation does not strengthen the influence of strategic orientation on SIP, indicating that external collaboration does not strengthen the influence of strategic orientation on SIP in this context..

Structural Model Quality Criteria

The structural model quality indicators are presented in Table 5. All variance inflation factor (VIF) values are below the commonly accepted threshold of 5, indicating that multicollinearity is not a concern. Although entrepreneurial and technological orientations exhibit relatively higher VIF values, they remain within acceptable limits.

The model shows strong explanatory power, with an adjusted R^2 value of 0,773, suggesting that a substantial proportion of variance in sustainable innovation performance is explained by the predictors.

Effect size (f^2) analysis indicates that environmental orientation has a large effect ($f^2 \geq 0,35$), while the remaining variables demonstrate small effects ($f^2 \geq 0,02$). This suggests that, although multiple strategic orientations contribute to innovation performance, environmental orientation plays a more dominant role within the model. Overall, these findings confirm that the model is statistically robust and provides meaningful explanatory insight into sustainable innovation performance in MSMEs.

Predictive Performance Evaluation

The predictive performance of the model was assessed using PLS-Predict and CVPAT, as summarized in Table 6. The Q^2_predict results indicate that the model has predictive relevance for sustainable innovation performance. The PLS-Predict results suggest that the model achieves an acceptable level of prediction accuracy. This is further supported by the CVPAT analysis, which shows that PLS-SEM performs significantly better than the indicator average (IA), while no significant difference is observed when compared to the linear model (LM). Taken together, these findings indicate that the model possesses adequate predictive capability. Although its performance is comparable to that of the linear benchmark, it remains effective in capturing the relationships within the data, particularly in the context of a more complex structural model.

ANN Architecture

An Artificial Neural Network (ANN) model was developed to capture nonlinear relationships in the data, complementing the explanatory analysis conducted using PLS-SEM. The model uses latent variable scores derived from the PLS-SEM analysis as input variables, representing the dimensions of strategic orientation, while sustainable innovation performance (SIP) is specified as the continuous target output.

Table 5 Structural model quality

Latent Variable	VIF	f^2	R^2 adjusted	Inference
SIP			0,773***	
CO	2,985	0,082		Small effect
ENO	1,917	0,523***		Large effect
EO	4,166	0,023		Small effect
LO	2,864	0,033		Small effect
TO	3,733	0,093		Small effect
OI x ENO	1,748	0,000		No effect
OI x LO	2,233	0,006		No effect
OI x CO	2,058	0,006		No effect
OI x EO	2,648	0,005		No effect
OI x TO	2,357	0,000		No effect

*** (significant at 0,001)

Table 6 predictive relevance evaluation

	Evaluation	PLS-SEM	Comparison	Average loss difference	Inference
PLS Predict	Q^2predict	0,754			Predictive relevance
	RMSE	0,501			
	MAE	0,414			
CVPAT	IA	0,228***	0,435	-0,207	Predictive validity established
	LM	0,228	0,237	-0,010	

*** (significant at 0,001)

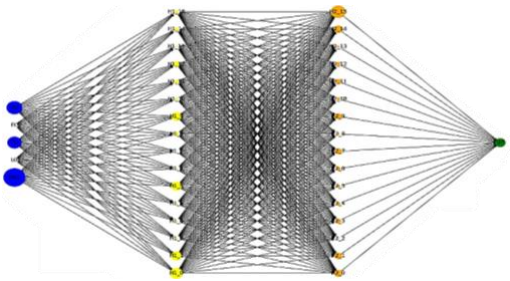

Figure 3 ANN architecture

The network adopts a multi-layer architecture consisting of an input layer, two hidden layers, and an output layer, as illustrated in Figure 3, The hidden layers incorporate activation functions, batch normalization, and dropout mechanisms to enhance model stability and reduce overfitting. This configuration enables the model to learn complex patterns and generate reliable predictions.

Hyperparameter Tuning

To obtain an optimal model configuration, hyperparameter tuning was performed using Bayesian optimization, as summarized in Table 7. The selected model corresponds to the configuration that achieved the lowest validation loss, reflecting a balance between predictive accuracy and generalization capability. This optimized configuration serves as the basis for subsequent model evaluation and validation.

Table 7 Hyperparameter configuration

No.	Best Configuration	Value
1	Trial ID	58
2	units_input	16
3	activation_input	relu
4	dropout_input	0,5
5	num_layers	1
6	units_1	112
7	l2_regularization	0,0001
8	activation_1	tanh
9	dropout_1	0,3
10	optimizer	rmsprop
11	learning_rate	0,01
12	units_2	336
13	activation_2	Relu
14	dropout_2	0,4
15	Val Loss	0,16333

The model performance was evaluated using K-fold cross-validation (K=5), as presented in Table 8. The results indicate consistent performance across folds, with relatively stable error metrics and coefficient of determination values, suggesting that the model generalizes well across different data subsets. This is further supported by the model loss curves (Figure 4), which show convergence between training and validation loss, indicating that the model achieves a good balance between underfitting and overfitting.

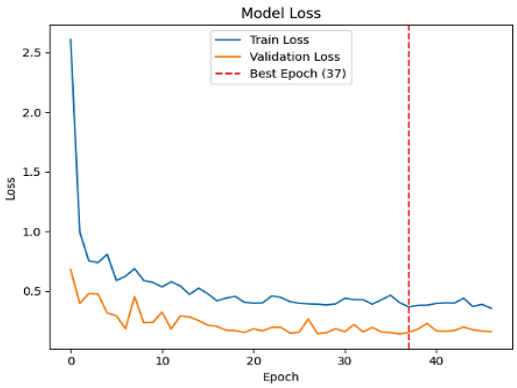

Figure 4 Model loss plot

Table 8 K-fold cross validation

Fold	RMSE	MSE	MAE	R^2
1	0,50919	0,25928	0,41748	0,71457
2	0,47038	0,22126	0,37848	0,778
3	0,46308	0,21445	0,36551	0,79629
4	0,5766	0,33247	0,47304	0,70479
5	0,44115	0,19462	0,35874	0,78878
Average	0,4921	0,2444	0,3986	0,7565
±STD	±0,0532	±0,0545	±0,0474	±0,0434

The predictive capability of the model is reflected in the comparison between predicted and actual values, as illustrated in Figure 5. The results indicate a strong fit between predicted and observed values, suggesting that the model is able to capture the underlying patterns in the data effectively. In the training data, the model explains 74,8% of the variance (R^2 = 0,748), while in the test data, the explanatory power increases to 85,4% (R^2 = 0,854), indicating good generalization performance without signs of overfitting. These findings suggest that the model maintains consistency when applied to unseen data, supporting its predictive reliability.

Table 9 Bootstrap metric error test data

Metric	Test Value	95% CI Lower	95% CI Upper
MSE	0,13716	0,08339	0,20399
MAE	0,30391	0,24007	0,37957
R^2	0,85402	0,73296	0,91665
RMSE	0,37035	0,28877	0,45165

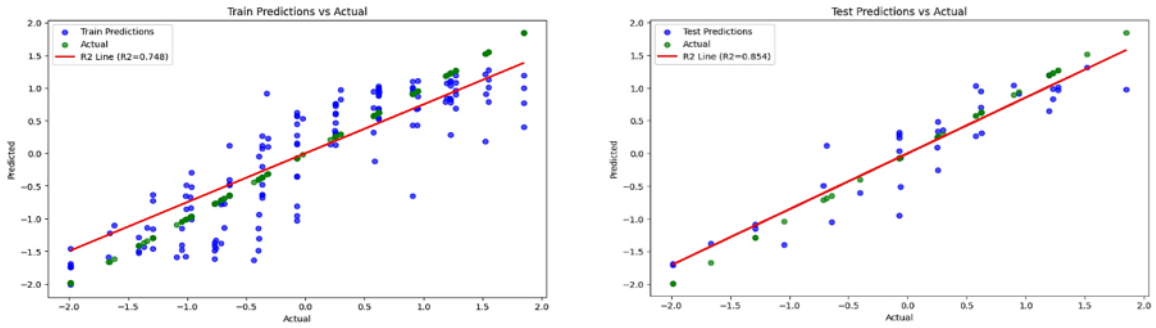

Figure 5 Actual vs prediction plot

To further assess the robustness of the model, a bootstrap procedure with 1,000 resamples at a 95% confidence level was conducted, as presented in Table 9. The results show that all performance metrics fall within their respective confidence intervals, confirming the stability of the model's predictive performance. In particular, the R^2 and RMSE values remain within narrow confidence bounds, indicating that the model consistently captures the relationship between input variables and the predicted output. This supports the reliability of the model in generating accurate predictions across different data samples

Relative Feature Importance

The relative feature importance results are presented in Figure 6 and detailed in Table 10. In this analysis, the ANN model uses latent variable scores of strategic orientations as input variables and predicts sustainable innovation performance (SIP) as a continuous output. Thus, the relative importance values reflect the contribution of each input variable to the prediction of SIP, rather than indicating causal relationships.

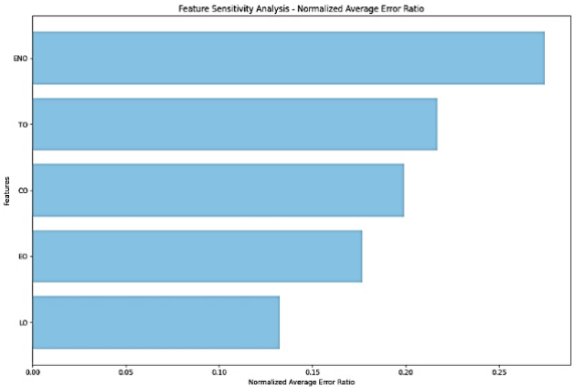

Figure 6 Relative feature importance

Table 10 Relative feature importance

Feature	Average Error Ratio	Feature	Normalized Average Error Ratio
ENO	1,94728	ENO	0,27462
TO	1,54865	TO	0,21695
CO	1,40706	CO	0,19918
EO	1,24915	EO	0,17668
LO	0,93796	LO	0,13256

The results show that environmental orientation has the highest contribution to the prediction of SIP, followed by technological and customer orientations. Entrepreneurial and learning orientations exhibit relatively lower contributions within the predictive model. These findings suggest that environmental and technological orientations play a more prominent role in shaping the predicted outcomes of sustainable innovation performance, while the remaining variables contribute to a lesser extent. This result complements the PLS-SEM findings by providing additional insight into the relative predictive influence of each variable.

Strategic Orientations and Sustainable Innovation Performance

The findings of this study indicate that Technological Orientation (TO), Environmental Orientation (ENO), Customer Orientation (CO), and Entrepreneurial Orientation (EO) exhibit significant positive relationships with Sustainable Innovation Performance (SIP), whereas Learning Orientation (LO) demonstrates a significant negative relationship. These results are consistent with RBV and DCT, which emphasize the role of strategic orientations in shaping SMEs' ability to innovate sustainably and respond to evolving market and regulatory demands. TO demonstrates a significant positive relationship with SIP by enhancing operational efficiency, reducing resource

consumption, and optimizing technological capabilities, ultimately supporting both competitiveness and sustainability (Braccini and Margherita 2019).

Likewise, ENO is positively linked to SIP, as integrating environmental considerations into innovation—such as adopting low-emission technology and sustainable materials—can improve market positioning and regulatory compliance (Elhaj 2024). CO also shows a significant positive relationship with SIP, as aligning innovation with consumer preferences for sustainability (e.g., organic materials and eco-friendly packaging) enhances market appeal (Mishra et al. 2024). Similarly, EO contributes positively to SIP by fostering risk-taking, proactiveness, and innovation, enabling SMEs to adapt to sustainability trends and explore emerging opportunities with agility (Yadav et al. 2024). Conversely, LO demonstrates a significant negative relationship with SIP, as it may lead to inefficiencies when not effectively aligned with sustainability objectives. While LO facilitates knowledge acquisition, its impact on SIP depends on whether internal learning is effectively directed toward sustainability-driven innovation. However, process innovation may help mitigate this challenge by ensuring that learning efforts contribute to operational improvements and resource efficiency (Widya-Hasuti et al. 2018).

The study finds no significant moderating effect of Open Innovation (OI) in the relationship between strategic orientations and SIP. Although OI is commonly associated with the exchange of external knowledge, practical challenges—such as difficulties in aligning external insights with internal strategies, the cost of adopting green technology, and limited access to strategic partners—may reduce its effectiveness (Aslam et al. 2025). This aligns with (Bogers et al. 2019), which suggest that external knowledge integration and organizational culture transformation often pose substantial challenges without a structured approach. However, targeted collaborations with sustainability-focused institutions and local stakeholders may still serve as complementary avenues for strengthening SIP.

To further assess predictive patterns, an Artificial Neural Network (ANN) model was employed, demonstrating strong predictive capability and providing complementary insights to the PLS-SEM results. The ANN model achieved a high coefficient of determination (R^2 = 85,4%) and low validation loss, indicating reliable prediction performance. These results indicate that ANN effectively captures nonlinear relationships within SIP predictors, without implying causal relationships, as shown in Table 11.

Table 11 Model performance

	RMSE	MAE	MSE	R^2
PLS-ANN	0,370	0,304	0,137	0,854
PLS-SEM	0,501	0,414	0,251	0,773

These findings align with Devianto et al. (2023), who emphasize the ability of ANN to model complex data interactions. Additionally, they are consistent with Kim et al. (2016), which highlights ANN's capability to capture nonlinear patterns in business environments. This underscores ANN's value in strategic innovation research, as it provides additional predictive insight into the relationships among variables.

From a theoretical perspective, this study extends the Resource-Based View (RBV) and Dynamic Capabilities Theory (DCT) by demonstrating how strategic orientations contribute to sustainable innovation performance through the effective utilization of internal capabilities. The findings also align with the Triple Bottom Line (TBL) perspective, emphasizing the integration of economic, environmental, and social considerations in shaping innovation outcomes. Environmental, technological, and customer orientations emerge as key contributors, while entrepreneurial orientation shows a more limited role and learning orientation reflects a context-dependent effect. This supports Lopes et al. (2022), who argue that sustainability-focused enterprises typically adopt innovative technologies and practices that enhance economic performance, strategic positioning, and market competitiveness. Furthermore, these findings enhance our understanding of LO's potential limitations, emphasizing that misaligned internal learning processes may hinder sustainability-focused innovation.

From a practical standpoint, this study provides valuable strategic insights for SMEs and policymakers, suggesting that prioritizing TO, ENO, CO, and EO can significantly enhance sustainable innovation outcomes. Additionally, it underscores the need for a more adaptive approach to LO, ensuring that knowledge acquisition and internal experimentation align with sustainability objectives rather than impeding them. Finally, the integration of PLS-ANN as a hybrid predictive methodology offers a more data-driven approach to

strategic decision-making, providing a robust foundation for SMEs to refine their innovation strategies and enhance long-term sustainability.

CONCLUSION

This study shows that environmental, technological, entrepreneurial, and customer orientations play a positive role in shaping sustainable innovation performance (SIP), with environmental orientation emerging as the most influential factor. In contrast, learning orientation exhibits a negative relationship with SIP, indicating that its role may not always align with expected theoretical assumptions and may depend on specific contextual conditions. Open innovation does not significantly moderate these relationships, suggesting that internal strategic capabilities remain more critical for MSMEs operating under resource constraints.

From a predictive perspective, the ANN results reinforce the importance of environmental, technological, and customer orientations, while also indicating that learning orientation still contributes to the predictive model despite its negative effect. This suggests that some relationships may not be fully captured through linear assumptions alone. Overall, the findings highlight the complementary roles of PLS-SEM and ANN, where PLS-SEM explains the direction and significance of relationships, and ANN provides additional insight into predictive patterns and variable importance. Practically, MSMEs should prioritize strengthening internal strategic orientations—particularly environmental and technological capabilities—while aligning external innovation efforts with their internal readiness to support sustainable innovation outcomes.

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