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Strategic Prioritization for Sustainable Livestock Production Systems: An Integrated SWOT–PLS-SEM Approach in Samarinda, Indonesia

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Abstract. *Rapid changes in urban areas create challenges for sustainable livestock development, including limited production resources and the need to balance economic, social, institutional, and ecological functions. This study develops an integrated SWOT–PLS-SEM framework to examine how Strength, Weakness, Opportunity, and Threat contribute to four TOWS strategy groups—SO, ST, WO, and WT—in supporting sustainable livestock production systems. The model was tested using 88 observations, eight constructs, and 40 indicators. All indicators showed high outer loadings ranging from 0.906 to 0.971, while composite reliability ranged from 0.967 to 0.984 and AVE from 0.855 to 0.925. Discriminant validity was supported by HTMT, with a maximum value of 0.857. All structural paths were positive and significant: Opportunity→SO (β=0.559), Strength→SO (β=0.451), Strength→ST (β=0.427), Threat→ST (β=0.606), Opportunity→WO (β=0.485), Weakness→WO (β=0.548), Threat→WT (β=0.440), and Weakness→WT (β=0.593). R^2 values ranged from 0.804 to 0.826, indicating high explanatory power. Predictive assessment produced Q^2predict values of 0.793–0.819, while CVPAT indicated that PLS-SEM prediction performance was significantly better than the average-indicator benchmark. The findings demonstrate that internal and external factors should be evaluated as measurable relationships rather than merely listed in a conventional SWOT analysis. The proposed framework provides a quantitative basis for prioritizing livestock development strategies, particularly in strengthening institutional capacity, improving production infrastructure, promoting crop–livestock integration, enhancing resource efficiency, and addressing environmental and policy challenges.*

Keywords: *Land-use dynamics, Livestock production systems, Sustainability assessment, Strategic prioritization, SWOT–PLS-SEM*

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INTRODUCTION

Land-use change reshapes the relationship between production activities, ecosystem services, and territorial sustainability. In livestock systems, it not only reduces available land but also affects production-space connectivity, feed access, infrastructure, land-use conflicts, and ecological functions. Livestock systems are increasingly challenged by competition for land and water, environmental pressures, and the need for context-specific development strategies (Dumont et al., 2019a; Genest-Richard, Halde, et al., 2025) . However, livestock production can also support ecosystem services through grazing systems, crop–livestock integration, and effective landscape management. (Pulido-Herrera et al., 2024a) highlighted landscape connectivity as an important factor in maintaining ecological functions in extensive livestock systems. These findings emphasize the importance of integrating spatial considerations into sustainable livestock-development planning.

SWOT analysis is widely used in regional development planning to identify internal and external factors, namely Strength, Weakness, Opportunity, and Threat. However, conventional SWOT analysis is primarily diagnostic and does not quantify the contribution of each factor to strategic alternatives. (Büyüközkan & Ilıcak, 2019) emphasized that interactions among SWOT factors can influence strategic priorities. Integrating SWOT with structural modeling therefore provides a quantitative basis for prioritizing SO, ST, WO, and WT strategies. Partial Least Squares Structural Equation Modeling (PLS-SEM) is suitable for this purpose because it evaluates relationships among latent constructs while assessing measurement quality, particularly in complex, prediction-oriented models (Akter et al., 2017). Clear conceptual specification of strategy constructs is also essential to ensure valid interpretation (Sarstedt et al., 2019) . Accordingly, this study treats S, W, O, and T as first-order constructs and SO, ST, WO, and WT as strategy constructs influenced by combinations of SWOT factors, following the SWOT–SEM approach (Mert et al., 2026; Ramadan et al., 2022) .

A research gap remains in the limited integration of land-use dynamics, SWOT factors, and livestock-development strategies within a single quantitative framework. Previous land-suitability studies have considered land use, environmental conditions, topography, road accessibility, and socio-economic criteria in livestock planning (Alturk et al., 2022) . However, these studies generally emphasize spatial suitability, while

institutional capacity, farmer capabilities, policy opportunities, and external threats are not always linked quantitatively to strategic priorities. In Indonesia, crop–livestock integration offers opportunities to improve productivity and sustainability, although its adoption remains constrained by knowledge, skills, policy support, and extension services (Kebebe, 2019a). urthermore, livestock-development scenarios may increase production while also raising land demand and emissions, highlighting the need to consider production–environment trade-offs (Brandt et al., 2020) . Therefore, sustainable livestock development requires simultaneous consideration of internal strengths, weaknesses, external opportunities, and threats.

Accordingly, this study aims to: (1) develop an integrated SWOT–PLS-SEM model to examine the relationships between S, W, O, and T and the SO, ST, WO, and WT strategies; (2) assess the validity and reliability of the measurement model; (3) evaluate the magnitude and significance of relationships between SWOT factors and strategic constructs; and (4) translate the structural results into strategic priorities for sustainable livestock production-zone development in Samarinda. The main contribution is to transform conventional SWOT analysis from a descriptive inventory into a testable relational framework that supports quantitative strategic prioritization.

LITERATURE REVIEW

Sustainable livestock production systems require a balance between productivity, economic viability, environmental protection, social well-being, and institutional capacity. Livestock farming contributes to food security, rural livelihoods, and agricultural development, but its sustainability depends on how production resources are managed and integrated with broader agricultural and ecological systems. (Dumont et al., 2019b) emphasized that livestock farming generates multiple goods, environmental impacts, and ecosystem services, indicating that livestock sustainability should be evaluated beyond production and economic performance. Similarly, (Genest-Richard, Devillers, et al., 2025) highlighted the contribution of alternative livestock farming practices to agroecological sustainability through improved resource management and environmental integration. These perspectives demonstrate that sustainable livestock development requires an integrated approach that considers production efficiency, resource availability, environmental performance, and the capacity of farming communities to adapt to changing conditions.

The sustainability of livestock systems is also influenced by the interaction between livestock production and other agricultural activities. Integrated crop–livestock systems offer opportunities to improve resource efficiency through the utilization of agricultural residues, recycling of nutrients, and diversification of farm production. (Oosting et al., 2021a) discussed the potential of livestock production within tropical circular food systems, emphasizing resource cycling and the integration of agricultural components. (He et al., 2023) further demonstrated that livestock production scenarios can influence both productivity and greenhouse gas mitigation, highlighting the importance of considering environmental trade-offs when developing livestock systems. Therefore, sustainable livestock development should not focus exclusively on increasing production capacity but should also strengthen resource efficiency, environmental management, and the resilience of agricultural systems.

At the institutional and social levels, livestock sustainability depends on farmer capabilities, access to technology, extension services, infrastructure, and supportive policies. (Kebebe, 2019b) identified innovation-system constraints as important barriers to technology adoption in livestock production, while emphasized the relevance of farm-scale indicators for evaluating sustainability in mixed crop–ruminant systems. These findings suggest that livestock sustainability is multidimensional and requires coordination among farmers, government institutions, agricultural organizations, and other stakeholders. Consequently, evaluating livestock development requires an analytical framework capable of considering internal capacities and external conditions simultaneously.

The development of sustainable livestock production systems is influenced by interconnected internal and external factors. Internal conditions include the availability of production resources, farmer knowledge and experience, institutional capacity, technological adoption, infrastructure, and the ability to integrate livestock with crop production. External conditions involve government policies, investment opportunities, market demand, technological developments, environmental pressures, and competition for agricultural resources. These factors interact to determine the capacity of livestock production systems to maintain productivity and respond to emerging challenges. (Dumont et al., 2019b) emphasized the multiple functions and impacts of livestock farming, while (Genest-Richard, Devillers, et al., 2025) highlighted the importance of

adapting livestock practices to ecological and resource conditions. Together, these studies indicate that livestock development strategies should account for both productive capacity and broader sustainability considerations.

Farmer capacity and institutional support are particularly important in determining the effectiveness of livestock-development initiatives. (Kebebe, 2019b) demonstrated that technology adoption in livestock systems is influenced by the broader innovation environment, including knowledge, institutional arrangements, and access to supporting services. Similarly, (Nazhira, 2025) (2025) identified limitations in farmer knowledge, technical skills, and institutional support as barriers to implementing improved livestock practices. These findings indicate that the availability of external opportunities, such as government programs, investment, and technological innovations, does not automatically produce better livestock-development outcomes. Such opportunities must be supported by adequate internal capabilities, infrastructure, and institutional coordination.

Environmental and economic pressures also influence strategic choices in livestock development. (Brandt et al., 2020) showed that livestock intensification may generate production and environmental trade-offs, suggesting that development strategies should consider resource efficiency and environmental consequences. (Oosting et al., 2021b) further emphasized the importance of circular resource utilization in tropical livestock systems. These perspectives support the need for strategies that strengthen existing production capacities while reducing environmental pressures and improving resource utilization. Accordingly, the SO, ST, WO, and WT strategy groups provide a useful framework for translating internal and external conditions into development priorities. However, identifying these factors is not sufficient; their relative contributions to strategic alternatives must also be evaluated to support evidence-based decision-making.

RESEARCH METHODS

Research Design and Study Context

The study was designed as an exploratory quantitative study to examine relationships between SWOT factors and livestock-zone development strategies in Samarinda City, East Kalimantan, Indonesia. A spatial perspective was used because livestock production is strongly dependent on land and location, while SWOT–SEM-PLS was used to explain how internal and external conditions shape strategic priorities. In the empirical implementation, spatio-temporal analysis is intended to identify land-

cover/land-use changes and livestock production zones over multiple observation years using remote sensing and GIS. Previous studies indicate that satellite-image classification, landscape variables, and multi-criteria analysis can be combined to evaluate livestock suitability and development risks (Palaniyandi et al., 2021) . Because the numerical remote-sensing outputs are not included in the SEM dataset analysed in this version, the spatio-temporal component is presented as the contextual basis for factor identification rather than as a claimed quantitative land-classification result.

Population, Unit of Analysis, and Data

The study population consisted of stakeholders with relevant knowledge, experience, interests, or involvement in livestock-area management and development, land use, spatial planning, environmental management, and agricultural and livestock development in Samarinda City. This population included local government officials, extension and technical personnel, livestock farmers or business groups, academics/researchers, and other stakeholders familiar with land-use dynamics and livestock-zone development. The population was selected because the study required specific assessments of internal and external conditions in livestock production areas. Respondents were not asked only for general perceptions; they evaluated Strength, Weakness, Opportunity, Threat, and the SO, ST, WO, and WT strategy constructs. Therefore, respondents were required to have relevant knowledge or experience of the research context.

Purposive sampling was used, with respondents selected according to predefined criteria aligned with the research objectives. Respondents were required to: (1) have knowledge or experience in livestock production, agriculture, spatial planning, environmental management, regional development, or policies relevant to livestock development; (2) understand land-use conditions and livestock-business or livestock-zone development in Samarinda; and (3) be willing to assess internal factors, external factors, and alternative livestock-zone strategies. Based on these criteria, 88 respondents were used as the sample for the SEM-PLS analysis. These 88 observations were used to examine relationships among four SWOT-factor constructs—Strength, Weakness, Opportunity, and Threat—and four strategy constructs—Strength–Opportunity (SO), Strength–Threat (ST), Weakness–Opportunity (WO), and Weakness–Threat (WT). Each construct was measured using five indicators, resulting in eight constructs and 40

indicators. Purposive sampling was considered appropriate because the study required respondents with contextual knowledge rather than a general population sample, consistent with previous SWOT–SEM research involving knowledgeable stakeholders (Utomo et al., 2021) .

Operationalization of SWOT and Strategy Constructs

The study model consisted of four SWOT-factor constructs—Strength (S), Weakness (W), Opportunity (O), and Threat (T)—and four strategy constructs—SO, ST, WO, and WT. Each construct was measured using five reflective indicators on a five-point Likert scale. Operational definitions are presented in Table 1.

Table 1. Operationalization of SWOT and Strategy Constructs

Code	Construct	Main dimensions/indicators
S	Strength	availability of suitable zones/land; local feed; farmer capacity; crop–livestock integration; institutions
W	Weakness	land conversion; fragmentation; infrastructure; technology/information; governance
O	Opportunity	GIS and remote sensing; spatial planning; livestock–agriculture integration; programs/investment; demand
T	Threat	land-use change; competition for space; environmental degradation; policy uncertainty; climate/disaster risks
SO	SO Strategy	leveraging strengths to capture opportunities
ST	ST Strategy	using strengths to address threats
WO	WO Strategy	reducing weaknesses by leveraging opportunities
WT	WT Strategy	minimizing weaknesses and controlling threats

Each indicator was scored on a five-point Likert scale, with higher scores representing better conditions or stronger capacity according to the direction of the construct. For Weakness and Threat, the measurement direction was framed as the capacity or readiness to respond to weaknesses and threats, so higher scores indicate stronger response capacity. This directional treatment was used to maintain consistent interpretation of structural coefficients and to avoid reversing the meaning between SWOT factors and strategies. SO, ST, WO, and WT represent strategies formed from combinations of internal and external factors: SO links Strength with Opportunity, ST links Strength with Threat, WO links Weakness with Opportunity, and WT links Weakness with Threat. This approach follows the SWOT–SEM framework used to prioritize strategies through relationships among factors (Siad et al., 2026) .

SEM-PLS Analysis Procedure

Data were analysed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS software. The analysis consisted of two stages:

measurement-model evaluation (outer model) and structural-model evaluation (inner model). The outer model was assessed using outer loadings, Cronbach's alpha, composite reliability (CR), and Average Variance Extracted (AVE). Convergent validity was evaluated using AVE, while discriminant validity was assessed using the Heterotrait–Monotrait Ratio (HTMT) as recommended by Henseler et al. (2015). Multicollinearity was assessed using Variance Inflation Factor (VIF) at both indicator and construct levels. The inner model was evaluated using path coefficients (β), t-statistics, p-values, bootstrap confidence intervals, R^2, f^2, and inner VIF. Significance was determined using bootstrapping. R^2 was used to assess how well exogenous constructs explain endogenous constructs, while f^2 was used to evaluate the relative contribution of each predictor (Avkiran, 2018). Predictive performance was further assessed using PLSpredict and the Cross-Validated Predictive Ability Test (CVPAT). PLSpredict evaluates out-of-sample prediction through a holdout procedure, while CVPAT compares prediction loss against benchmark models. This predictive assessment is important because a model with high R^2 does not necessarily have strong predictive performance (Li, 2017) .

Integration of SEM-PLS with the TOWS Matrix

The SEM-PLS findings were integrated with the TOWS matrix to prioritize livestock-zone development strategies. Integration considered the direction and magnitude of path coefficients (β), statistical significance, f^2, and the explanatory power of each strategy construct. Factors with stronger effects and larger effect sizes were given higher priority as the basis for strategy formulation. The results were translated into four strategy groups: SO, ST, WO, and WT. SO focuses on leveraging strengths to capture opportunities; ST uses strengths to address threats; WO reduces weaknesses by exploiting opportunities; and WT minimizes weaknesses while controlling threats. The resulting strategies were translated into spatially relevant actions, including protection of production land, fragmentation control, crop–livestock integration, infrastructure and technology improvement, institutional strengthening, and climate and land-use-change adaptation.

Through this approach, SWOT is not used only to identify internal and external factors; it is combined with SEM-PLS to quantify relationships and prioritize strategies. The framework also allows strategy results to be linked back to spatio-temporal land-use

conditions so that recommendations become more operational and relevant for livestock production-zone planning.

RESULTS AND DISCUSSION

1. Measurement Model Quality: Indicator Consistency and Convergent Validity

The measurement-model results are presented in Table 2. The table shows that all 40 indicators used to measure the eight constructs—Strength (S), Weakness (W), Opportunity (O), Threat (T), and strategies SO, ST, WO, and WT—had outer loadings ranging from 0.906 to 0.971. The lowest loading was observed for the W construct (0.906), while the highest loading was 0.971 for ST. The loading ranges were 0.927–0.940 for S, 0.906–0.951 for W, 0.930–0.951 for O, 0.907–0.938 for T, 0.953–0.968 for SO, 0.926–0.971 for ST, 0.945–0.961 for WO, and 0.943–0.959 for WT. All indicators therefore exceeded the commonly accepted 0.70 threshold, indicating that each indicator adequately represented its latent construct. (Hair et al., 2019) explain that loadings of approximately 0.70 or higher indicate an adequate contribution to the construct, while higher values indicate stronger explanatory power.

Table 2 also shows very high internal consistency. Cronbach's alpha ranged from 0.958 to 0.980, while composite reliability ranged from 0.967 to 0.984. S and W each had Cronbach's alpha of 0.963 and CR of 0.971. SO had the highest values, with alpha=0.980 and CR=0.984. Threat had the lowest reliability values among the constructs, but they remained very high (alpha=0.958; CR=0.967). (Adriani et al., 2020; Hair et al., 2019) consider values above 0.70 acceptable, while values above approximately 0.95 should be examined for possible item redundancy. Thus, the instrument demonstrates strong consistency, but the wording and content of highly correlated items should still be examined during empirical validation. AVE values in Table 2 ranged from 0.855 to 0.925, far above the 0.50 minimum criterion. Threat had the lowest AVE (0.855), whereas SO had the highest (0.925). This means that each construct explained at least 85.5% of the variance in its indicators, providing strong evidence of convergent validity. (Purwanto & Sudargini, 2021) state that an AVE of 0.50 or greater indicates that a construct explains more than half of the variance in its indicators. Accordingly, both the SWOT-factor constructs and the strategy constructs met the convergent-validity requirement.

Table 2. Measurement Model Assessment of SWOT Factors and Strategy Constructs

Construct	Outer Loading Range	Cronbach's α	Composite Reliability (CR)	AVE
Strength (S)	0.927–0.940	0.963	0.971	0.870
Weakness (W)	0.906–0.951	0.963	0.971	0.870
Opportunity (O)	0.930–0.951	0.966	0.974	0.881
Threat (T)	0.907–0.938	0.958	0.967	0.855
Strategy SO	0.953–0.968	0.980	0.984	0.925
Strategy ST	0.926–0.971	0.972	0.978	0.898
Strategy WO	0.945–0.961	0.975	0.981	0.910
Strategy WT	0.943–0.959	0.973	0.979	0.901

The strong measurement results in Table 2 also show that SO, ST, WO, and WT can be treated as measurable latent constructs rather than merely conceptual categories within a SWOT matrix. This is important because conventional SWOT analysis often produces a list of internal and external factors without revealing statistical relationships among them. (Perdana et al., 2026) demonstrated that integrating SWOT with structural equation modeling allows S, W, O, and T to be treated as latent constructs and then used to form SO, ST, WO, and WT strategies. The results therefore provide a quantitative basis for proceeding to structural-model evaluation. From a livestock-sustainability perspective, the use of multiple indicators is also theoretically justified because livestock systems are multidimensional and involve production, environmental, social, economic, technological, institutional, and adaptive dimensions. (Leite et al., 2024) similarly emphasized the importance of farm-scale indicators across multiple dimensions for assessing sustainability in mixed crop–ruminant systems.

Nevertheless, the very high loadings, alpha, and composite reliability should be interpreted cautiously. The SO construct, for example, has CR=0.984 and AVE=0.925, indicating extremely strong consistency but also the possibility that some items are substantively redundant. (Marcatto et al., 2022) stress that measurement quality is not determined by reliability alone; each indicator should also contribute unique substantive information. Subsequent instrument refinement should therefore pay attention to content validity to ensure that SO, ST, WO, and WT indicators represent distinct strategic dimensions. Overall, Table 2 supports the adequacy of the measurement model and provides a basis for discriminant-validity and structural-model assessment.

2. Discriminant Validity and Multicollinearity Issues

After convergent validity and reliability were established, discriminant validity and multicollinearity were evaluated. The results are presented in Tables 3 and 4. These assessments are important to ensure that Strength (S), Weakness (W), Opportunity (O),

Threat (T), SO, ST, WO, and WT represent distinct concepts and do not suffer from excessive linear dependence.

Table 3. Discriminant Validity Assessment Using the HTMT Criterion

Parameter	Result
Maximum HTMT value	0.857
Construct pair with highest HTMT	W–WT
Conservative threshold	0.85
Common threshold	0.90
Decision	Acceptable with caution

As shown in Table 3, the maximum HTMT value was 0.857 for the relationship between Weakness (W) and WT strategy. This value is slightly above the conservative 0.85 threshold but remains below the 0.90 threshold that is often considered acceptable for conceptually related constructs. (Ab Hamid et al., 2017) proposed HTMT as a more sensitive criterion for discriminant-validity assessment than the Fornell–Larcker criterion and cross-loadings. Thus, 0.857 warrants attention but does not provide strong evidence that W and WT are empirically identical. The close association is also conceptually understandable because W describes internal limitations, whereas WT describes a defensive strategy intended to reduce the effects of weaknesses under external threats. Nevertheless, the two constructs must remain functionally distinct: W asks what the internal weaknesses are, whereas WT asks what strategies are used to reduce those weaknesses under threat.

The HTMT value between Opportunity and SO is also conceptually close to the threshold. This is understandable because SO is explicitly designed to exploit opportunities through internal strengths. In TOWS terms, Opportunity is an external condition, whereas SO is the strategic response to that condition. Therefore, high conceptual proximity does not automatically imply a theoretical problem, but indicators must retain distinct definitions and measurement functions. (Rönkkö & Cho, 2022) emphasize that discriminant validity should be supported not only statistically but also conceptually. Overall, Table 3 indicates that the model can still distinguish the SWOT and strategy constructs, although item wording should avoid excessive overlap, particularly for closely related pairs such as W–WT and O–SO.

Table 4. Inner VIF Values for Assessing Structural Multicollinearity

Predictor Path	Inner VIF
S → SO	1.580
O → SO	1.580
S → ST	1.321
T → ST	1.321
W → WO	1.405
O → WO	1.405
W → WT	1.402
T → WT	1.402
Range	1.321–1.580

Table 4 shows that all inner VIF values ranged from 1.321 to 1.580. These values are low and indicate no serious structural multicollinearity. (Jumaisa et al., 2026) note that low VIF values imply that predictor constructs do not have excessive overlap that would destabilize path-coefficient estimates. This is important because each strategy construct is explained by two SWOT factors. For example, SO is simultaneously predicted by Strength and Opportunity, yet their VIF of 1.580 indicates sufficiently distinct information for relatively stable estimation. The same pattern applies to ST, WO, and WT. Therefore, differences in path coefficients can be interpreted as relative differences in factor contribution rather than as artefacts of excessive predictor correlation.

However, inner VIF should be distinguished from outer VIF. Some measurement indicators show outer VIF values above 5, particularly for several strategy indicators and some Opportunity and Strength indicators. This points to possible indicator redundancy rather than structural multicollinearity. (Hair et al., 2020) explain that very high correlations among indicators within a construct can produce elevated indicator VIF and suggest that items may be measuring nearly identical information. For example, an item referring to “land availability” should be distinguished from one referring to “capacity to protect land”, while “government programs” should be distinct from “institutional capacity to use government programs”. Such distinctions strengthen content validity and reduce statistical redundancy. Overall, Tables 3 and 4 indicate acceptable discriminant validity and no serious structural multicollinearity, while also highlighting the need for indicator refinement in empirical implementation.

3. Structural Effects of Opportunity and Strength on the SO Strategy

After the measurement model met the reliability, convergent-validity, and discriminant-validity criteria, the structural model was evaluated to determine the relative contribution of the SWOT factors to the TOWS strategy constructs. The first focus was the SO strategy, which combines internal strengths with external opportunities. Figure 1 presents the estimated PLS-SEM model, showing the relationships between the SWOT factors and the four TOWS strategy constructs, together with the outer loadings, structural path coefficients, and R^2 values.

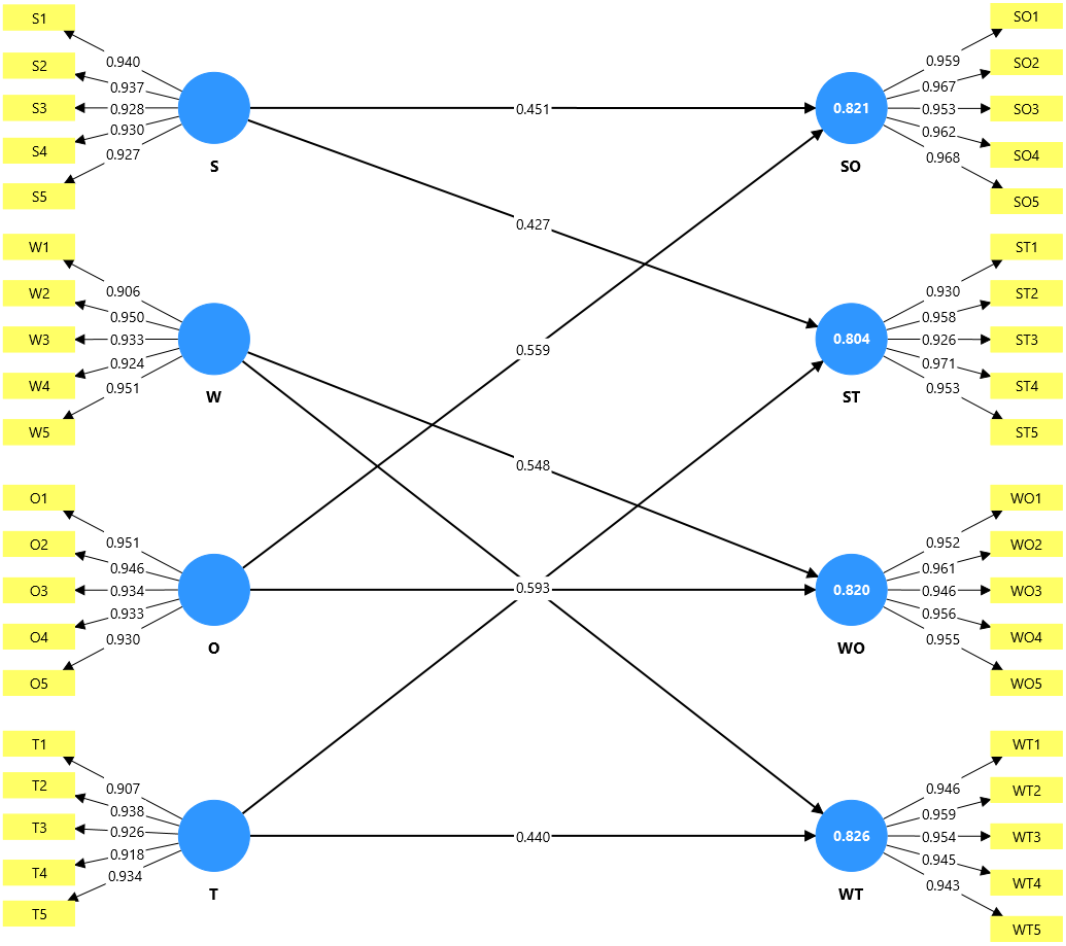


Figure 1. Structural Relationships Between SWOT Factors and TOWS Strategy Constructs

Figure 1 shows that all eight structural relationships are positive, indicating that stronger internal capacities, greater opportunities, and stronger readiness to respond to weaknesses and threats are associated with stronger TOWS strategies. The structural path coefficients also show differences in the relative contribution of each SWOT factor.

Among the four endogenous strategy constructs, the R^2 values range from 0.804 to 0.826, indicating that the corresponding SWOT predictors explain a substantial proportion of the variance in each strategy construct. The strongest structural relationship is Threat→ST (β=0.606), followed by Weakness→WT (β=0.593), Opportunity→SO (β=0.559), and Weakness→WO (β=0.548). These results indicate that external threats and internal weaknesses are particularly important drivers of strategic responses. The detailed structural results for the SO strategy are presented in Table 5.

Table 5. Structural Model Results for the SO Strategy

Path	β	t-statistic	p-value	95% CI	f^2	Decision
O → SO	0.559	10.021	<0.001	0.439–0.660	1.105	Significant
S → SO	0.451	7.889	<0.001	0.337–0.562	0.721	Significant

SO has an R^2 of 0.8212 and adjusted R^2 of 0.8170. Strength and Opportunity therefore explain approximately 82.12% of the variance in SO strategy. (Plonsky & Ghanbar, 2018) note that higher R^2 reflects stronger explanatory power, provided that the value is interpreted within the study context. Table 5 further shows that Opportunity has the strongest effect on SO (β=0.559; t=10.021; p<0.001), with a 95% bootstrap confidence interval of 0.439–0.660 that remains entirely above zero. The f^2 value of 1.105 indicates a large effect. In other words, stronger opportunities and stronger capacity to exploit them are associated with stronger SO strategies. Strength also has a positive and significant effect on SO (β=0.451; t=7.889; p<0.001; 95% CI 0.337–0.562; f^2=0.721). Thus, both SO hypotheses are supported, although Opportunity is relatively more dominant than Strength. This is consistent with the SWOT–SEM framework of (Islam, 2024) , in which SO represents the strategic combination of internal strengths and external opportunities. SEM makes it possible to quantify the relative contribution of each factor rather than merely list factors in a SWOT matrix.

In livestock production zones, the dominance of Opportunity indicates substantial external space for strategic development, but such opportunities must be connected to local strengths. Opportunities include GIS and remote-sensing technologies, government support and investment, livestock-area policies, crop–livestock integration, and growing demand for livestock products. However, these opportunities are difficult to exploit without suitable land, local feed resources, farmer experience, integration potential, and

functioning institutions. This interpretation is consistent with (Tiny et al., 2026) , who show that integrated crop–livestock systems can support productivity and sustainability but require human capacity, knowledge, extension, policy support, and institutional arrangements. The spatial dimension reinforces this argument. (Legese et al., 2025) demonstrated that livestock development planning requires multi-criteria land-suitability assessment, including land use, environmental conditions, and accessibility. Therefore, the SO strategy should be translated into GIS-based priority-zone development rather than simple livestock expansion. (Argote et al., 2022) likewise highlighted landscape connectivity in livestock systems. Land availability alone does not guarantee sustainability if production areas are fragmented and functionally disconnected. In this study, Strength in terms of land availability should therefore be protected through spatial planning, while Opportunity in the form of GIS can be used to map connectivity and identify priority areas.

From an investment-policy perspective, the higher coefficient for Opportunity (β=0.559) than Strength (β=0.451) suggests that government programs and investments should be explicitly linked to local capacities. Infrastructure, for example, should be developed in areas with genuine resource strength and economic prospects rather than only in locations that are administratively convenient. Overall, Table 5 indicates a strong statistical foundation for SO strategy, with high R^2 and significant paths. In Samarinda, this means developing GIS-based livestock priority zones, integrating local feed resources with crop–livestock systems, strengthening farmer institutions, and targeting investment toward areas that are spatially and ecologically suitable.

4. Dominance of Threat in the ST Strategy

The relationships between Strength, Threat, and ST strategy are presented in Table 6. ST is a strategy that uses internal strengths to address or reduce external threats. The strategy has an R^2 of 0.8040 and adjusted R^2 of 0.7993, meaning that Strength and Threat explain approximately 80.40% of the variance in ST. This indicates high explanatory power.

Table 6. Structural Model Results for the ST Strategy

Path	β	t-statistic	p-value	95% CI	f^2	Decision
T → ST	0.606	10.820	<0.001	0.484–0.705	1.417	Significant
S → ST	0.427	6.741	<0.001	0.296–0.546	0.704	Significant

Threat has the strongest effect on ST (β=0.606; t=10.820; p<0.001; 95% CI 0.484–0.705). The f^2 value of 1.417 is one of the largest in the entire model. This indicates that stronger external pressure is associated with a stronger need to develop ST strategies based on internal strengths. Strength also has a positive and significant effect on ST (β=0.427; t=6.741; p<0.001; 95% CI 0.296–0.546; f^2=0.704). Thus, both hypotheses are supported, but Threat is relatively more dominant than Strength.

This finding is consistent with the basic TOWS principle: ST strategies are developed when a system uses existing strengths to address external threats. In this study, strengths such as available production land, local feed resources, farmer experience, crop–livestock integration potential, and institutions can function as adaptive capital when livestock zones face land-use pressure. (Kent et al., 2018) likewise modelled Strength and Threat jointly as predictors of ST strategies. The key contribution is that SEM shows which factor contributes more strongly rather than only listing the factors.

The dominance of Threat is particularly relevant in areas experiencing rapid land-use change. Threats include land conversion, competition for space with settlements and economic activities, landscape fragmentation, environmental degradation, spatial-policy uncertainty, and climate or disaster risks. When such threats increase, simple production expansion becomes less adequate. A more resilient approach uses local assets and capacities to maintain core production functions while limiting spatial and environmental pressure.

The spatial perspective is crucial. (Said et al., 2016) showed that landscape connectivity is important in extensive livestock systems because fragmentation and human pressure can reduce ecological function. Accordingly, the T→ST relationship can be translated into protecting core livestock areas, maintaining connectivity among production zones, and avoiding expansion into high-conservation-value areas. The SEM result should therefore be linked to land-use maps so that "Threat affects ST" becomes a spatially targeted intervention rather than a generic recommendation.

The ST strategy should also recognize production–environment trade-offs. (Enahoro et al., 2019) showed that livestock-development scenarios can raise output while also increasing land demand and environmental pressure unless efficiency and resource management improve. Therefore, the high Threat coefficient should not be

interpreted as an argument to stop livestock development. Instead, it signals the need to increase productivity in appropriate locations while reducing additional pressure on space and the environment. Policy priorities include protecting strategic livestock zones, controlling fragmentation, strengthening adaptive farmer capacity, and improving cross-sector coordination.

5. WO Strategy: Opportunities as a Mechanism for Addressing Weaknesses

The WO strategy is designed to reduce internal weaknesses by exploiting external opportunities. Results for Weakness and Opportunity are shown in Table 7. WO has an R^2 of 0.8198 and adjusted R^2 of 0.8155, meaning that Weakness and Opportunity jointly explain approximately 81.98% of the variance in WO strategy.

Table 7. Structural Model Results for the WO Strategy

Path	β	t-statistic	p-value	95% CI	f^2	Decision
W → WO	0.548	7.931	<0.001	0.401–0.671	1.185	Significant
O → WO	0.485	7.003	<0.001	0.346–0.617	0.928	Significant

Weakness has a positive and significant effect on WO (β=0.548; t=7.931; p<0.001; 95% CI 0.401–0.671), with f^2=1.185. Opportunity also has a positive and significant effect (β=0.485; t=7.003; p<0.001; 95% CI 0.346–0.617), with f^2=0.928. Both effect sizes are large, but Weakness has the stronger contribution. The result indicates that WO is driven primarily by the need to improve internal conditions and is then strengthened by the external opportunities available. In the operationalization used here, higher Weakness scores represent stronger readiness or capacity to address weaknesses. Therefore, the positive W→WO coefficient indicates that stronger readiness to address internal weaknesses is associated with stronger WO strategies. This is consistent with the TOWS logic in which WO strategies are used when internal limitations coexist with opportunities that can be mobilized to improve the system. (Manley et al., 2024) showed that SEM can be used to quantify the relative contributions of Weakness and Opportunity to WO strategies.

In Samarinda's livestock production zones, weaknesses include land fragmentation, inadequate infrastructure, limited technology and information, and weak governance and coordination. If these conditions persist, the livestock sector will have difficulty maintaining production functions under continued land-use change. The WO result

therefore suggests that policy should focus on closing internal capacity gaps rather than merely exploiting external opportunities. External opportunities include GIS and remote sensing, spatial-planning instruments, crop–livestock integration, government programs and investment, and market demand. These opportunities become effective only when they are linked to specific weaknesses. GIS, for example, should not merely produce maps; it should help solve weaknesses in spatial organization and fragmentation. Likewise, investment should be directed to infrastructure bottlenecks that constrain livestock production zones.

The result is consistent with (Nazhira, 2025) , who identified knowledge and skill gaps, policy constraints, and weak dissemination as barriers to integrated crop–livestock adoption in Indonesia, and who emphasized technical guidance, extension, training, field demonstrations, credit access, and incentives. Thus, WO strategy should combine technology interventions with human-resource and institutional strengthening. The land-use dimension further supports this interpretation. Fragmentation cannot be addressed through physical infrastructure alone. It requires coordination among spatial zoning, accessibility, roads, water, feed locations, and markets. (Qiu et al., 2017) showed that livestock development planning requires multi-criteria suitability assessment. Accordingly, GIS should be used to direct opportunities toward locations where structural weaknesses can be reduced. Jónsdóttir and Gísladóttir (2023) similarly argued that land-use planning, food production, and rural development are interconnected and should not be planned separately (Bousbaine, 2017) . In this study, WO strategy therefore implies synchronization of livestock zoning with transport networks, water sources, feed centers, agricultural areas, and markets.

Spatial targeting is important because weaknesses are not evenly distributed. Some locations may have severe fragmentation but good market access, whereas others may have abundant land but poor infrastructure. SEM identifies Weakness as the dominant WO driver, while GIS can identify where the weaknesses are greatest and where opportunities for intervention are strongest. This is consistent with (Pulido-Herrera et al., 2024b) , who emphasized the role of landscape connectivity. WO strategies can therefore include consolidation of production zones, improved connecting infrastructure, spatial-technology adoption, and institutional strengthening. Table 7 also shows that Weakness has a higher effect size (f^2=1.185) than Opportunity (f^2=0.928). This indicates that WO is

driven more by the need to solve internal constraints than by the mere availability of external opportunities. Therefore, large opportunities will not generate optimal outcomes if internal weaknesses remain unresolved. This has a direct policy implication: government programs and investments should be preceded by a clear diagnosis of internal needs in each livestock production zone.

6. WT Strategy as a Defensive Strategy

The WT strategy minimizes internal weaknesses while controlling the impact of external threats. The results are shown in Table 8. WT has an R^2 of 0.8258 and adjusted R^2 of 0.8217, meaning that Weakness and Threat together explain 82.58% of the variance in WT. This is the highest R^2 among SO, ST, WO, and WT, showing that internal vulnerabilities and external pressures provide a particularly strong explanation of defensive-strategy formation.

Table 8. Structural Model Results for the WT Strategy

Path	β	t-statistic	p-value	95% CI	f^2	Decision
W → WT	0.593	11.638	<0.001	0.489–0.687	1.441	Significant
T → WT	0.440	7.675	<0.001	0.323–0.548	0.794	Significant

Weakness has the strongest effect on WT (β=0.593; t=11.638; p<0.001; 95% CI 0.489–0.687), with f^2=1.441—the largest effect size in the model. Threat also has a positive and significant effect (β=0.440; t=7.675; p<0.001; 95% CI 0.323–0.548; f^2=0.794). Thus, both predictors are important, but Weakness contributes more strongly. The result indicates that WT is primarily formed by internal vulnerability and then intensified by external pressure. This finding follows the TOWS logic of defensive strategy: WT is relevant when internal limitations coexist with a threatening external environment. (Fagarazzi et al., 2026) showed that modelling WT through SEM allows Weakness and Threat to be evaluated simultaneously rather than prioritizing strategies subjectively. In the current context, the strong W→WT path suggests that reducing internal vulnerability should precede broad expansion or scale-up.

In livestock production zones, such weaknesses may include land fragmentation, inadequate infrastructure, limited technology and information, and weak governance and coordination. When these weaknesses meet land-use conversion, competition for space, environmental degradation, spatial-policy uncertainty, and climate change, system

vulnerability increases. WT therefore should not be interpreted as a strategy to stop livestock production, but as a strategy to protect the remaining production function and prevent further loss of carrying capacity. Jaisli and Brunori (2024) emphasize balancing efficiency, sufficiency, circularity, and resource constraints in future livestock systems. Accordingly, defensive strategies should focus on improving land, feed, water, infrastructure, and labor efficiency before encouraging further expansion. From a spatial perspective, WT is particularly important because land-use change can have cumulative effects. Fragmentation not only reduces land area; it can disrupt links between production land, feed, water, roads, and markets, thereby increasing transport and production costs and reducing system flexibility. (Pulido-Herrera et al., 2024b) emphasize that landscape connectivity influences ecological function and adaptive capacity. The strong W→WT effect implies that area protection should begin with identifying internal vulnerability hotspots. A zone may look suitable on a map but remain functionally vulnerable if road access, water, or institutional support are inadequate. SEM should therefore be combined with GIS so that high-impact weaknesses can be mapped and defensive interventions geographically prioritized.

WT also requires land-use conflict mitigation. Where livestock zones face settlement expansion, industrial development, or infrastructure projects, unclear boundaries can accelerate conversion. Defensive strategies should therefore include formal designation of livestock production zones, spatial-policy alignment, protection of strategically important land, and stronger cross-sector coordination.

7. Comparison of Strategy Strength and Priority Implications

As illustrated in Figure 1, the four TOWS strategies are driven by different combinations of internal and external SWOT factors. The comparative analysis in Table 9 further identifies the relative strength of these structural relationships and their implications for strategy prioritization. After analysing each strategy group, the next step is to compare the relative strength of all structural paths. This comparison is important because the purpose of SWOT–SEM integration is not only to test whether relationships are significant, but also to identify which factors provide the greatest relative contribution to each strategy. The complete results are shown in Table 9.

Table 9. Comparison of Structural Path Strength and Strategy Priorities

Path	β	t-statistic	p-value	95% CI	f^2
T → ST	0.606	10.82	<0.001	0.484–0.705	1.417
W → WT	0.593	11.64	<0.001	0.489–0.687	1.442
O → SO	0.559	10.02	<0.001	0.439–0.660	1.105
W → WO	0.548	7.93	<0.001	0.401–0.671	1.185
O → WO	0.485	7.00	<0.001	0.346–0.617	0.928
S → SO	0.451	7.89	<0.001	0.337–0.562	0.721
T → WT	0.440	7.68	<0.001	0.323–0.548	0.794
S → ST	0.427	6.74	<0.001	0.296–0.546	0.704

Table 9 shows that all structural paths are positive and significant at $p<0.001$. Path coefficients range from 0.427 to 0.606, indicating positive contributions of all SWOT factors to their corresponding strategies. However, effect strength differs. The largest path is Threat→ST (β=0.606), followed by Weakness→WT (β=0.593), Opportunity→SO (β=0.559), and Weakness→WO (β=0.548). The smallest path is Strength→ST (β=0.427). This pattern shows that threats and weaknesses are the strongest drivers of strategic responses. T→ST and W→WT also have large f^2 values of 1.417 and 1.442, respectively, indicating that external pressure and internal vulnerability are particularly important when the system formulates protection and adaptation strategies. The result suggests that policy should not focus only on opportunity exploitation. If land conversion and competition for space intensify while internal weaknesses remain high, growth-oriented strategies may actually increase system vulnerability. This interpretation is consistent with (Jin et al., 2026) , who demonstrated that SEM-based SWOT can differentiate strategy priorities using the relationships and relative contributions of factors rather than relying solely on SWOT weights.

On the opportunity side, O→SO (β=0.559; f^2=1.105) shows that Opportunity is the most important factor for SO. This indicates substantial development space through technology, policy, investment, crop–livestock integration, and markets. However, the strong Threat and Weakness effects in ST and WT indicate that these opportunities should be exploited after protection and internal capacity have received adequate attention. Accordingly, three priority levels can be distinguished. First is protective-adaptive strategy, especially ST, because Threat is the strongest predictor. Second is vulnerability-reduction strategy, especially WT and WO, because Weakness has strong effects on both. Third is opportunity-exploitation strategy, especially SO, by developing areas that combine strong resource potential with suitable market or policy opportunities.

This sequence is more rational than conventional SWOT, where factors are often placed in a matrix without information about their relative contribution to strategies. SEM-PLS allows prioritization using path coefficients, effect sizes, significance, and explanatory power. This represents an important methodological contribution. In Samarinda, the implication is that livestock-zone development should begin with protection of remaining production space, followed by productivity improvement and economic-opportunity utilization. (Qiu et al., 2017) emphasized that livestock development planning requires comprehensive spatial suitability assessment. Therefore, areas associated with high strategy coefficients should be linked to locations with high land-use pressure or high vulnerability. (Oosting et al., 2021b) also argue that livestock sustainability requires balance among efficiency, sufficiency, circularity, and resource availability. High strategic coefficients therefore should not automatically be translated into maximum output expansion, but into interventions that reduce pressure and improve efficiency under limited resources.

8. Predictive Performance of the Model

In addition to evaluating the model's explanatory power through R^2, predictive performance was assessed using PLSpredict and CVPAT. PLSpredict results are shown in Table 10.

Table 10. Predictive Performance of Endogenous Strategy Constructs

Construct	Q^2predict	RMSE	MAE
SO	0.815	0.438	0.328
ST	0.793	0.463	0.364
WO	0.810	0.445	0.345
WT	0.819	0.435	0.349

Table 10 shows positive Q^2predict values for all endogenous strategy constructs: 0.815 for SO, 0.793 for ST, 0.810 for WO, and 0.819 for WT. These values indicate relevant predictive performance. WT has the highest Q^2predict (0.819), while ST has the lowest (0.793), although all remain high. In terms of prediction error, WT has the lowest RMSE (0.435), while ST has the highest (0.463). SO has the lowest MAE (0.328), whereas ST has the highest (0.364). Lower RMSE and MAE indicate lower prediction error. The results suggest relatively consistent prediction of all four strategies, although with some differences in error magnitude. These findings are important because a high R^2 alone does not prove strong predictive ability. (Shmueli et al., 2019) recommend out-

of-sample predictive assessment because a highly explanatory model may still perform poorly on new observations. The positive Q^2predict values and low prediction errors therefore provide additional evidence that the SWOT–SEM model can predict strategy-related outcomes, not merely explain relationships within the estimation sample.

WT is especially notable because it has the highest Q^2predict and the lowest RMSE. This is consistent with its high structural R^2 (0.8258) and the strong W→WT effect (β=0.593). In contrast, ST has the lowest Q^2predict and relatively higher RMSE and MAE. One possible explanation is that ST responds strongly to Threat, which represents dynamic external factors such as land-use change, spatial competition, policy changes, and environmental risk. Such factors may be less predictable than internal characteristics. Therefore, external uncertainty may partly explain the higher prediction error for ST. The predictive findings have practical implications: the model may be used as a decision-support tool but should not be interpreted as an absolute forecasting system. High predictive performance suggests that the observed relationships are sufficiently stable to support planning, but policy changes, market conditions, and land-use dynamics may require periodic model updating.

9. CVPAT Evaluation

CVPAT results show that PLS-SEM prediction loss is lower than the average-indicator benchmark for all strategy constructs. Loss differences are approximately −1.590 for SO, −1.388 for ST, −1.540 for WO, and −1.533 for WT, with all p-values far below 0.001. This indicates statistically lower prediction error for the PLS-SEM model compared with the benchmark. The result reinforces PLSpredict by showing that predictive performance is not merely a consequence of sample variation but also represents an advantage relative to a simple benchmark model. (Sharma et al., 2023) recommend benchmark comparison to establish whether a PLS-SEM model provides incremental predictive value. Overall, the PLSpredict and CVPAT findings indicate two main strengths: high explanatory power (R^2=0.804–0.826) and strong predictive ability (positive Q^2predict values and lower prediction error than the benchmark). Nevertheless, model performance depends on the quality and stability of its constructs and indicators. If spatial, policy, or market conditions change substantially, the model should be updated. In the empirical implementation, PLSpredict should therefore be combined with Sentinel-

2/GIS monitoring so that strategy recommendations can be updated as spatial conditions change.

Overall, the PLSpredict and CVPAT results support the predictive adequacy of the model. The SWOT–SEM framework therefore serves not only to evaluate relationships among factors, but also as a decision-support tool for prioritizing livestock production-zone strategies under changing spatial and environmental conditions.

CONCLUSION

This study developed an integrated SWOT–PLS-SEM framework to prioritize sustainable livestock production-zone development strategies. All structural relationships were positive and significant, with path coefficients ranging from 0.427 to 0.606 and R^2 values from 0.804 to 0.826, indicating strong explanatory power. Threat was the strongest driver of ST, while Weakness dominated WT and WO. Meanwhile, Opportunity showed the strongest contribution to SO. These findings highlight the importance of addressing internal weaknesses and external threats while utilizing available strengths and opportunities in livestock development. The strategic priorities include strengthening production capacity, improving infrastructure and institutional coordination, promoting crop–livestock integration, enhancing resource efficiency, and increasing adaptability to environmental and policy challenges. The integration of SWOT and PLS-SEM provides a quantitative approach to evaluating strategic relationships and prioritizing development interventions beyond conventional descriptive SWOT analysis.

This study is limited by the use of simulated data for model testing rather than empirical field-survey observations. Therefore, the findings demonstrate the analytical applicability of the proposed framework but cannot yet be generalized to actual livestock-sector conditions in Samarinda. Future research should validate the model using empirical stakeholder data to strengthen its reliability and practical application in sustainable livestock development.

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REFERENCES

Ab Hamid, M. R., Sami, W., & Mohmad Sidek, M. H. (2017). Discriminant Validity Assessment: Use of Fornell & Larcker criterion versus HTMT Criterion. Journal of Physics: Conference Series, 890(1), 012163. https://doi.org/10.1088/1742-6596/890/1/012163

Adriani, M., Malahias, M. A., Gu, A., Kahlenberg, C. A., Ast, M. P., & Sculco, P. K. (2020). Determining the Validity, Reliability, and Utility of the Forgotten Joint Score: A Systematic Review. The Journal of Arthroplasty, 35(4), 1137–1144. https://doi.org/10.1016/J.ARTH.2019.10.058

Akter, S., Fosso Wamba, S., & Dewan, S. (2017). Why PLS-SEM is suitable for complex modelling? An empirical illustration in big data analytics quality. Production Planning & Control, 28(11–12), 1011–1021. https://doi.org/10.1080/09537287.2016.1267411

Alturk, B., Kurc, H. C., Konukcu, F., & Kocaman, I. (2022). Multi-criteria land use suitability analysis for the spatial distribution of cattle farming under land use change modeling scenarios in Thrace Region, Turkey. Computers and Electronics in Agriculture, 198, 107063. https://doi.org/10.1016/J.COMPAG.2022.107063

Argote, K., Rodríguez-Sánchez, B., Quintero, M., & Francesconi, W. (2022). One Tree at a Time: Restoring Landscape Connectivity through Silvopastoral Systems in Transformed Amazon Landscapes. Diversity, 14(10), 846. https://doi.org/10.3390/D14100846/S1

Avkiran, N. K. (2018). Rise of the partial least squares structural equation modeling: An application in banking. International Series in Operations Research and Management Science, 267, 1–29. https://doi.org/10.1007/978-3-319-71691-6_1/SAVE-RESEARCH

Bousbaine, A. U. de L.-Ul. > Doct. sc. (géog. -paysage). (2017). What can agricultural land use planning contribute to food production and food policy. International Journal of Avian and Wildlife Biology, Vol 2 issue 1(1). https://doi.org/10.15406/IJAWB.2017.02.00009

Brandt, P., Yesuf, G., Herold, M., & Rufino, M. C. (2020). Intensification of dairy production can increase the GHG mitigation potential of the land use sector in East Africa. Global Change Biology, 26(2), 568–585. https://doi.org/10.1111/GCB.14870

Büyüközkan, G., & Ilıcak, Ö. (2019). Integrated SWOT analysis with multiple preference relationsSelection of strategic factors for social media. Kybernetes, 48(3), 451–470. https://doi.org/10.1108/K-12-2017-0512

Dumont, B., Ryschawy, J., Duru, M., Benoit, M., Chatellier, V., Delaby, L., Donnars, C., Dupraz, P., Lemauviel-Lavenant, S., Méda, B., Vollet, D., & Sabatier, R. (2019a). Review: Associations among goods, impacts and ecosystem services provided by

livestock farming. Animal, 13(8), 1773–1784. https://doi.org/10.1017/S1751731118002586

Dumont, B., Ryschawy, J., Duru, M., Benoit, M., Chatellier, V., Delaby, L., Donnars, C., Dupraz, P., Lemauviel-Lavenant, S., Méda, B., Vollet, D., & Sabatier, R. (2019b). Review: Associations among goods, impacts and ecosystem services provided by livestock farming. Animal, 13(8), 1773–1784. https://doi.org/10.1017/S1751731118002586

Enahoro, D., Mason-D'Croz, D., Mul, M., Rich, K. M., Robinson, T. P., Thornton, P., & Staal, S. S. (2019). Supporting sustainable expansion of livestock production in South Asia and Sub-Saharan Africa: Scenario analysis of investment options. Global Food Security, 20, 114–121. https://doi.org/10.1016/J.GFS.2019.01.001

Fagarazzi, C., Andaloro, M., Cappelli, G., Marini, N., Olimpi, F., & Bernetti, I. (2026). Perceived Disorder, Fear of Crime, and Safety in Urban Parks: A Structural Equation Modeling Study from a Large Metropolitan Green Area in Florence, Italy. Urban Science, 10(3), 170. https://doi.org/10.3390/URBANSCI10030170/S1

Genest-Richard, P., Devillers, N., Halde, C., Tremblay, S., & Mundler, P. (2025). The humans behind the herd: are alternative livestock farms agroecological from a socioeconomic perspective? Journal of Rural Studies, 119, 103711. https://doi.org/10.1016/J.JRURSTUD.2025.103711

Genest-Richard, P., Halde, C., Mundler, P., & Devillers, N. (2025). A Promising Niche: Current State of Knowledge on the Agroecological Contribution of Alternative Livestock Farming Practices. Agriculture 2025, Vol. 15, Page 235, 15(3), 235. https://doi.org/10.3390/AGRICULTURE15030235

Hair, J. F., Howard, M. C., & Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. Journal of Business Research, 109, 101–110. https://doi.org/10.1016/J.JBUSRES.2019.11.069

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

He, D., Deng, X., Wang, X., & Zhang, F. (2023). Livestock greenhouse gas emission and mitigation potential in China. Journal of Environmental Management, 348, 119494. https://doi.org/10.1016/J.JENVMAN.2023.119494

Islam, M. S. (2024). Mobile Financial Service (MFS) in Bangladesh: A comprehensive study of different service providers.

Jin, S., Chang, L., Zhang, N. N., & Li, Y. (2026). Impact analysis of institutional framework and policy preferences with Bayesian structural equation. PLOS ONE, 21(9), e0358701. https://doi.org/10.1371/JOURNAL.PONE.0358701

Jumaisa, B, F. Z., & Faradiba, B. (2026). Family Environment, Local History Pedagogy, and Cultural Value Internalization: Associations with Heritage Preservation Attitudes in Parepare, Indonesia. JPI: Jurnal Pustaka Indonesia, 6(2), 542-563-542-563. https://doi.org/10.62159/JPI.V6I2.2774

Kebebe, E. (2019a). Bridging technology adoption gaps in livestock sector in Ethiopia: A innovation system perspective. Technology in Society, 57, 30–37. https://doi.org/10.1016/J.TECHSOC.2018.12.002

Kebebe, E. (2019b). Bridging technology adoption gaps in livestock sector in Ethiopia: A innovation system perspective. Technology in Society, 57, 30–37. https://doi.org/10.1016/J.TECHSOC.2018.12.002

Kent, D. M., Steyerberg, E., & Van Klaveren, D. (2018). Personalized evidence based medicine: predictive approaches to heterogeneous treatment effects. BMJ, 363. https://doi.org/10.1136/BMJ.K4245

Legese, B., Kalura, P., Degife, A., Godana, G., & Chamara, J. (2025). Integrating GIS and Multi-Criteria Analysis for Sustainable Livestock Grazing: A Holistic Assessment of Biophysical and Socio-Economic Determinants in Semi-Arid Dawa Watershed of Ethiopia. Land Degradation and Development, 36(13), 4626–4642. https://doi.org/10.1002/LDR.5658;REQUESTEDJOURNAL:JOURNAL:1099145X;WGROUP:STRING:PUBLICATION

Leite, F. F. G. D., Faverin, C., Ciganda, V. S., Cristobal-Carballo, O., dos Reis, J. C., Eugène, M., Fariña, S., Hercher-Pasteur, J., Monteiro, A., Pastell, M., Recavarren, P., Romera, A., Rosanowski, S., Tieri, M. P., Aubry, A., Veysset, P., Kenny, D., & Vibart, R. (2024). Relevance of farm-scale indicators and tools for farmers to assess sustainability of their mixed crop-ruminant livestock systems. Science of The Total Environment, 950, 175218. https://doi.org/10.1016/J.SCITOTENV.2024.175218

Li, J. (2017). Assessing the accuracy of predictive models for numerical data: Not r nor r2, why not? Then what? PLOS ONE, 12(8), e0183250. https://doi.org/10.1371/JOURNAL.PONE.0183250

Manley, S. C., Williams, R. I., & Hair, J. F. (2024). Enhancing TQM's effect on small business performance: a PLS-SEM exploratory study of TQM applied with a comprehensive strategic approach. The TQM Journal, 36(5), 1252–1272. https://doi.org/10.1108/TQM-10-2021-0299

Marcatto, F., Di Blas, L., Luis, O., Festa, S., & Ferrante, D. (2022). The Perceived Occupational Stress Scale: A Brief Tool for Measuring Workers' Perceptions of Stress at Work. European Journal of Psychological Assessment, 38(4), 293–306. https://doi.org/10.1027/1015-5759/A000677

Mert, İ., Yağlı, H., Costa, J., & Oliveira, A. P. (2026). A Hybrid NLP-SWOT and Economic Modeling Framework for Sustainable Hydrogen Policy: Assessing Türkiye's Clean Energy Transition and LCOH Projections. Sustainability (Switzerland), 18(15), 7506. https://doi.org/10.3390/SU18157506/S1

Nazhira, F. G. (2025). Barriers to Implementing Organic Waste-Based Fermented Feed Practices Among Livestock Farmers in Kuningan, West Java. Livestock Science & Innovation Journal, 2(2), 66–90. https://doi.org/10.59261/LSIJ.V2I2.29

Oosting, S., van der Lee, J., Verdegem, M., de Vries, M., Vernooij, A., Bonilla-Cedrez, C., & Kabir, K. (2021a). Farmed animal production in tropical circular food systems. Food Security 2021 14:1, 14(1), 273–292. https://doi.org/10.1007/S12571-021-01205-4

Oosting, S., van der Lee, J., Verdegem, M., de Vries, M., Vernooij, A., Bonilla-Cedrez, C., & Kabir, K. (2021b). Farmed animal production in tropical circular food systems. Food Security 2021 14:1, 14(1), 273–292. https://doi.org/10.1007/S12571-021-01205-4

Palaniyandi, M., Sharmila, T., Manivel, P., Thirumalai, P., & Anand, P. H. (2021). Multispectral Satellite Data and GIS for Mapping Vector Ecology, Monitoring, Risk Assessment, and Forecast of Vector Borne Disease Epidemics: A Systematic Review. Applied Ecology and Environmental Sciences, 9(8), 751–760. https://doi.org/10.12691/aees-9-8-6

Perdana, R. W., Indrayatie, E. R., Maulana, A. R., & Subagyo, R. (2026). Strategies for Improving Occupational Safety Culture at PT PLN Indonesia Power Generation Business Unit in the South Kalimantan and Central Kalimantan Work Areas. Jurnal Manajemen Motivasi, 22(1), 1348–1369. https://doi.org/10.29406/JMM.V22I1.8629

Plonsky, L., & Ghanbar, H. (2018). Multiple Regression in L2 Research: A Methodological Synthesis and Guide to Interpreting R2 Values. Modern Language Journal, 102(4), 713–731. https://doi.org/10.1111/MODL.12509;ISSUE:ISSUE:DOI

Pulido-Herrera, L. A., Sepulveda, C., Jiménez, J. A., Betanzos Simon, J. E., Pérez-Sánchez, E., & Niño, L. (2024a). Landscape connectivity in extensive livestock farming: an adaptive approach to the land sharing and land sparing dilemma. Frontiers in Sustainable Food Systems, 8, 1345517. https://doi.org/10.3389/FSUFS.2024.1345517/TEXT

Pulido-Herrera, L. A., Sepulveda, C., Jiménez, J. A., Betanzos Simon, J. E., Pérez-Sánchez, E., & Niño, L. (2024b). Landscape connectivity in extensive livestock farming: an adaptive approach to the land sharing and land sparing dilemma. Frontiers in Sustainable Food Systems, 8, 1345517. https://doi.org/10.3389/FSUFS.2024.1345517/TEXT

Purwanto, A., & Sudargini, Y. (2021). Partial Least Squares Structural Squation Modeling (PLS-SEM) Analysis for Social and Management Research : A Literature Review. Journal of Industrial Engineering & Management Research, 2(4), 114–123. https://doi.org/10.7777/JIEMAR.V2I4.168

Qiu, L., Zhu, J., Pan, Y., Hu, W., & Amable, G. S. (2017). Multi-criteria land use suitability analysis for livestock development planning in Hangzhou metropolitan area, China. Journal of Cleaner Production, 161, 1011–1019. https://doi.org/10.1016/J.JCLEPRO.2017.07.053

Ramadan, M., Amer, T., Salah, B., & Ruzayqat, M. (2022). The Impact of Integration of Industry 4.0 and Internal Organizational Forces on Sustaining Competitive Advantages and Achieving Strategic Objectives. Sustainability 2022, Vol. 14, Page 5841, 14(10), 5841. https://doi.org/10.3390/SU14105841

Rönkkö, M., & Cho, E. (2022). An Updated Guideline for Assessing Discriminant Validity. Organizational Research Methods, 25(1), 6–14. https://doi.org/10.1177/1094428120968614;PAGEGROUP:STRING:PUBLICATION

Said, M. Y., Ogutu, J. O., Kifugo, S. C., Makui, O., Reid, R. S., & de Leeuw, J. (2016). Effects of extreme land fragmentation on wildlife and livestock population abundance and distribution. Journal for Nature Conservation, 34, 151–164. https://doi.org/10.1016/J.JNC.2016.10.005

Sarstedt, M., Hair, J. F., Cheah, J. H., Becker, J. M., & Ringle, C. M. (2019). How to Specify, Estimate, and Validate Higher-Order Constructs in PLS-SEM. Australasian Marketing Journal, 27(3), 197–211. https://doi.org/10.1016/J.AUSMJ.2019.05.003

Sharma, P. N., Liengaard, B. D., Hair, J. F., Sarstedt, M., & Ringle, C. M. (2023). Predictive model assessment and selection in composite-based modeling using PLS-SEM: extensions and guidelines for using CVPAT. European Journal of Marketing, 57(6), 1662–1677. https://doi.org/10.1108/EJM-08-2020-0636

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J. H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. European Journal of Marketing, 53(11), 2322–2347. https://doi.org/10.1108/EJM-02-2019-0189

Siad, M. M., Ahmed, Y. A., & Shehzad, H. M. F. (2026). Factors Influencing Open Access Sustainability in Somali University Libraries: A SWOT-Based SEM Analysis. International Information & Library Review. https://doi.org/10.1080/10572317.2026.2704158

Tiny, G., Lucas, M. R., Marta-Costa, A., & Henriques, P. D. (2026). Sustainability and Family Farming Systems: A Mixed-Methods Analysis from a Small Island Developing State. Sustainability 2026, Vol. 18, Page 6796, 18(13), 6796. https://doi.org/10.3390/SU18136796

Utomo, S. B., Sekaryuni, R., Widarjono, A., Tohirin, A., & Sudarsono, H. (2021). Promoting Islamic financial ecosystem to improve halal industry performance in Indonesia: a demand and supply analysis. Journal of Islamic Marketing, 12(5), 992–1011. https://doi.org/10.1108/JIMA-12-2019-0259