



A Structural Performance Analysis Framework Integrating Balanced Scorecard and Interpretive Structural Modeling for Fruit-Processing Agroindustry Small and Medium-Sized Enterprises: Evidence From Indonesia

Imam Santoso¹, Rika Ampuh Hadiguna², Mohammad Fuad Fauzul Mu'tamar³, Izzum Wafi'uddin¹,
Naila Maulidina Lu'ayya¹, Rizkiyah Isnaini¹, Debrina Puspita Andriani^{4*}

¹ Department of Agro-Industrial Technology, Universitas Brawijaya, 65145 Malang City, Indonesia

² Department of Industrial Engineering, Universitas Andalas, 25175 Padang, Indonesia

³ Department of Agro-Industrial Technology, Universitas Trunojoyo Madura, 69162 Madura, Indonesia

⁴ Department of Industrial Engineering, Universitas Brawijaya, 65145 Malang City, Indonesia

* Correspondence: Debrina Puspita Andriani (debrina@ub.ac.id)

Received: 07-15-2026

Revised: 09-14-2026

Accepted: 09-17-2026

Citation: I. Santoso, R. A. Hadiguna, M. F. F. Mu'tamar, I. Wafi'uddin, N. M. Lu'ayya, R. Isnaini, and D. P. Andriani, "A structural performance analysis framework integrating balanced scorecard and interpretive structural modeling for fruit-processing agroindustry small and medium-sized enterprises: Evidence from Indonesia," *J. Eng. Manag. Syst. Eng.*, vol. 5, no. 4, pp. 461–482, 2026. <https://doi.org/10.56578/jemse050401>.



© 2026 by the author(s). Published by Acadlore Publishing Services Limited, Hong Kong. This article is available for free download and can be reused and cited, provided that the original published version is credited, under the CC BY 4.0 license.

Abstract: The fruit-processing agroindustry plays a strategic role in reducing post-harvest losses and enhancing agricultural value creation in developing countries. However, small and medium-sized enterprises (SMEs) in this sector face multidimensional operational challenges, necessitating a holistic and structural evaluation of their performance system rather than fragmented, financially oriented assessments. This study aimed to analyze the multidimensional performance and uncover the hierarchical interdependencies of performance indicators within fruit-processing agroindustry SMEs. The methodology employed a sequential mixed-method design integrating the balanced scorecard (BSC) and interpretive structural modeling (ISM) combined with cross-impact matrix multiplication applied to classification (MICMAC, from the French “matrice d’impacts croisés multiplication appliquée à un classement”) analysis. The framework evaluated two representative product typologies in Malang Raya, Indonesia: a dry-processing case (fruit chips) and a liquid-processing case (fruit juice). The comparative BSC results revealed distinct performance profiles; the dry-processing case demonstrated stronger financial performance, whereas the liquid-processing case excelled in customer satisfaction and asset turnover. Concurrently, both typologies exhibited a significant drop in quality control, characterized by negative scores on the number of defective products, driven by scaling production volume over capacity boundaries. The ISM analysis structured these cross-perspective metrics into a robust nine-level hierarchy, identifying the number of machines as the ultimate foundational driver possessing the highest driving power (DP) of 17 and minimal dependence power (D). The MICMAC matrix further isolated eight independent driving variables, nine dependent outcome variables, and two autonomous variables, with no linkage variables present. These findings indicate that long-term enterprise competitiveness is structurally anchored to basic machinery availability and workforce competency development rather than downstream marketing actions. Theoretically, this study extends the BSC into a structurally informed paradigm by mapping structural influence pathways under resource constraints. Practically, it provides managers and extension institutions with a systematic diagnostic sequence to prioritize infrastructure investments over uniformly distributed improvement efforts.

Keywords: Agroindustry small and medium-sized enterprises; Balanced scorecard; Fruit processing; Interpretive structural modeling; MICMAC analysis; Structural performance analysis

1 Introduction

Fruit-processing small and medium-sized enterprises (SMEs) operate under persistent managerial and operational constraints that require careful prioritization of limited financial, technological, and human resources. Managers must

simultaneously address production performance, equipment-related constraints, product quality, workforce capability, customer requirements, and financial outcomes, while determining which improvement actions should be addressed first. These challenges are particularly important in fruit-processing operations, where differences in processing systems and product characteristics can create distinct requirements for production control, quality management, and resource allocation. Consequently, performance management in fruit-processing SMEs is not merely a matter of monitoring business outcomes, but also an engineering-management problem involving the allocation of constrained resources and the sequencing of improvement actions within an interconnected performance system [1–3]. Within the broader agri-food context, these enterprises also contribute to reducing post-harvest losses, extending product shelf life, increasing agricultural value creation, and strengthening linkages between primary production and downstream markets [4, 5].

Effective performance control under such conditions requires a multidimensional assessment rather than reliance on financial indicators alone [6, 7]. The operational sustainability of fruit-processing SMEs depends on the simultaneous achievement of financial performance, customer expectations, internal process effectiveness, and organizational learning and capability development [3, 8]. A weakness in one dimension may constrain improvement in another because organizational performance is shaped by interactions among multiple operational and managerial dimensions [9, 10]. For example, limitations in workforce capability may affect process consistency, while operational deficiencies may influence product quality and downstream business outcomes [8, 10]. Therefore, managers require a performance measurement framework that can identify strengths and weaknesses across multiple organizational dimensions and provide a systematic basis for allocating limited resources to priority areas [3, 8]. The balanced scorecard (BSC), which integrates financial, customer, internal business process, and learning and growth perspectives, provides an appropriate multidimensional foundation for such an assessment [11].

However, multidimensional measurement alone does not indicate how performance indicators are structurally related or which indicators should receive managerial attention earlier than others. Performance indicators may interact across organizational perspectives rather than operate as isolated measures [9, 12]. Treating indicators as independent can therefore obscure the structural relationships through which resource- and capability-related factors are associated with operational and performance outcomes [12, 13]. This limitation becomes particularly important when managers face resource constraints and must determine an appropriate sequence of improvement rather than attempting to address all performance indicators simultaneously [8, 14]. Structural analysis can complement performance measurement by identifying directional relationships among indicators and distinguishing relatively influential indicators from more dependent outcomes [13, 14]. Interpretive structural modeling (ISM) provides such a mechanism by organizing complex relationships among system elements into a hierarchical structure based on expert judgment [13, 15]. Despite the complementary potential of BSC and ISM, multidimensional performance measurement and structural interdependency analysis have largely been applied separately, particularly in agroindustry SMEs. This separation limits conventional performance assessment to identifying what performs well or poorly, without sufficiently explaining how indicators are structurally positioned or how managerial attention may be sequenced under resource constraints.

To address this gap, this study integrates BSC and ISM in an exploratory two-case analysis of fruit-processing SMEs in Malang Raya, Indonesia. BSC is applied to assess case-specific performance profiles, while ISM provides a common expert-perceived structural reference for examining the hierarchical relationships among the selected performance indicators. The integration is intended to support structural interpretation and managerial sequencing rather than to establish causal relationships. Accordingly, this study addresses three research questions (RQs):

RQ1: What performance patterns are observed across the BSC perspectives in the two-representative fruit-processing case SMEs?

RQ2: How are the selected performance indicators hierarchically structured based on expert judgment?

RQ3: How can the structurally influential indicators identified through ISM inform the sequencing of managerial attention in the two case SMEs?

This study aims to develop an integrated performance evaluation framework that combines multidimensional performance assessment with structural analysis. The proposed framework extends conventional performance evaluation by linking case-specific performance patterns with an expert-perceived hierarchy of indicator relationships. In doing so, the study contributes to performance measurement literature by advancing a structurally informed approach while providing managers with a more systematic basis for directing limited resources toward priority areas and supporting long-term performance improvement.

2 Literature Review

2.1 Balanced Scorecard as a Multi-Perspective Performance Measurement Framework

BSC originates from Kaplan and Norton [11], who developed it as a multi-perspective performance system integrating financial, customer, internal business process, and learning and growth perspectives to translate strategy into measurable indicators; a bibliometric review of over a thousand studies confirms that these four perspectives

remain central to BSC research more than three decades later, alongside growing extensions toward sustainability and integrated reporting [11].

This robustness is reflected in the framework's sustained adoption well beyond its original corporate setting: systematic reviews document extensive BSC deployment in healthcare and mental health services, reporting measurable strategic-alignment benefits alongside consistent indicator clusters spanning clinical, staff, and governance dimensions, despite persistent implementation challenges [16, 17]. Within SMEs specifically, however, BSC adoption remains comparatively underexplored, with empirical evidence pointing to mixed outcomes: an investigation of SMEs in Francophone Africa found that adoption and implementation vary considerably, ranging from partial adoption of selected perspectives to full or adapted implementation shaped by organizational culture and socio-economic context, indicating that adoption barriers are not uniform across regions and that BSC-SME research to date remains geographically concentrated outside underexplored contexts such as Sub-Saharan Africa [18]. A further limitation, independent of organizational scale, concerns how the BSC treats key performance indicators (KPIs) once selected: the framework has been criticized for treating indicators as isolated metrics within their respective perspectives, overlooking the causal and structural interdependencies that shape leverage points and bottlenecks within performance systems [19, 20]. This motivates the integration of BSC with methods capable of explicitly mapping such interdependencies, as elaborated in the following section.

2.2 Interpretive Structural Modeling for Structural Interdependency Analysis

ISM originates from Warfield [15], who introduced it as a systematic methodology for structuring complex, poorly articulated problem systems into a multilevel hierarchical model. Through a structural self-interaction matrix (SSIM), reachability matrix construction, and iterative level partitioning, ISM transforms qualitative expert judgment into a rigorous representation of direct and indirect dependencies among a system's elements [15]. Building on this foundation, one cluster of studies has paired ISM with performance or decision frameworks across the service and manufacturing sectors: Dahooie et al. [21] integrated BSC perspectives with ISM and the analytic network process in healthcare; Moores et al. [20] applied structural modeling within a BSC framework in the performing arts sector; and Tudose et al. [19] provided complementary evidence from the automotive sector that financial KPIs are interdependent rather than independent. Second, geographically broader clusters apply ISM directly to agri-food and agroindustry systems: within Indonesia, ISM has mapped institutional actors and sustainability strategies in the coffee agribusiness and agroindustry, and supply chain sustainability more broadly [22, 23], while governance-oriented applications in Brazilian agribusiness and a fuzzy-cross-impact matrix multiplication applied to classification (MICMAC, from the French “matrice d'impacts croisés multiplication appliquée à un classement”) model for the Peruvian kiwicha supply chain confirm that this is a globally transferable approach rather than a regionally isolated one [24, 25]. However, none of these agri-food applications incorporate a structured, multi-perspective performance framework analogous to the BSC.

A third pattern emerges at the SME level, where ISM and BSC-adjacent frameworks have been applied separately rather than in combination: ISM has been used to rank the sustainability and Industry 4.0 adoption barriers SMEs face—factors closely paralleling BSC's operational and learning-and-growth dimensions—while BSC-type assessments and related performance frameworks have been applied to SME automation projects, green supply chain practices, and food-processing innovation without connecting either method to the other [26–28]. Taken together, the literature reveals three parallel but disconnected streams: structural modeling paired with BSC outside the agroindustry, ISM applied within agri-food systems without a multi-perspective performance framework, and ISM applied at the SME level without connecting it to BSC. Table 1 summarizes the positioning of these studies relative to the present research.

2.3 Research Gap

As shown in Table 1, despite growing recognition that performance indicators are structurally interdependent rather than isolated, and despite ISM's demonstrated value for mapping such interdependencies both within Indonesian agroindustry systems and at the SME level more broadly, no identified study integrates a multi-perspective performance measurement framework with structural interdependency modeling specifically for fruit-processing agroindustry SMEs. Existing integrative efforts combining performance measurement with structural modeling are confined to sectors outside the agroindustry, namely healthcare, performing arts, and automotive, where organizational scale, resource availability, and operational complexity differ substantially from those of SMEs. Meanwhile, ISM applications within agri-food and agroindustry systems have so far been directed at commodity- and sustainability-focused questions such as institutional actor mapping and supply chain sustainability, rather than at systematic, KPI-based performance measurement at the enterprise level. ISM applications at the SME level have been used to structure adoption barriers and operational challenges but have not been connected to a multi-perspective performance framework.

Table 1. Positioning of this study relative to related literature

Study	Sector/Context	Multi-Perspective Performance Measurement	Structural Interdependency Modeling	Small and Medium-Sized Enterprise (SME) Focus	Agroindustry Context
Dahooie et al. [21]	Healthcare	✓	✓	–	–
Moore et al. [20]	Performing arts	✓	✓	–	–
Tudose et al. [19]	Automotive	–	✓	–	–
Rico et al. [22]	Coffee agribusiness	–	✓	–	✓
Yani et al. [23]	Agroindustry supply chain	–	✓	–	✓
de Sena Silva et al. [24]	Agribusiness (governance)	–	–	–	✓
Najib et al. [28]	Food processing SME	–	–	✓	✓
Axmann and Harmoko [27]	SME projects using robotic process automation (RPA)	✓	–	✓	–
This study	Fruit-processing agroindustry	✓	✓	✓	✓

Note: “–” indicates that the corresponding criterion was not considered or was not applicable in the reviewed study. ✓ indicates that the corresponding criterion was considered in the reviewed study.

This three-way intersection combining a structured, multidimensional performance framework, a technique for mapping structural interdependencies among its indicators, and an SME-level agroindustry setting remains unaddressed in the reviewed literature. Closing this gap matters both theoretically and practically: theoretically, it extends the BSC beyond a static, perspective-isolated measurement tool toward a structurally informed framework capable of revealing which performance dimensions function as foundational drivers versus dependent outcomes; practically, it offers fruit-processing SMEs typically constrained in analytical resources and managerial capacity an interpretable basis for prioritizing improvement efforts rather than treating all KPIs as equally actionable. This study addresses this gap by integrating BSC-based performance measurement with ISM-based structural analysis for fruit-processing SMEs in Malang Raya, Indonesia.

3 Methods

3.1 Research Design and Case Selection

This study employed a multi-case, sequential mixed-method design integrating the BSC and ISM as a structural performance-analysis framework for fruit-processing agroindustry SMEs in Malang Raya, Indonesia (Figure 1). The study was designed as an exploratory comparison between two case SMEs representing contrasting processing contexts: one dry-processing case producing fruit chips and one liquid-processing case producing fruit juice. The case selection was intended to capture differences in operational and processing conditions rather than to represent two populations of enterprises or to support statistical generalization across the fruit-processing SME sector. Accordingly, the findings are interpreted as case-specific evidence within the investigated context. To provide contextual information for interpreting the exploratory comparison, the main characteristics of the two case SMEs are summarized in Table 2.

The analytical procedure consisted of two complementary stages. First, BSC assessment was conducted separately for each case SME to obtain case-specific performance profiles. Second, ISM was conducted once using a combined expert panel drawn from both processing contexts to construct a common, expert-perceived reference structure describing the hierarchical relationships among the selected performance indicators. Because the ISM structure was not developed separately for each enterprise, it should not be interpreted as evidence that the same relationships operate identically or with equal strength in both processing settings. Instead, the structure was used exploratorily as a shared reference for interpreting the position of case-specific performance strengths and weaknesses within the broader performance system.

The two case SMEs differ noticeably in business age, workforce size, processing equipment, and the period covered by their available records (Table 2). These differences reflect real variations in operating history and record-keeping practices across independently managed enterprises rather than a flaw in case selection, and they do not undermine the validity of the comparison for three reasons. First, the comparison is structural and pattern-based rather than point-estimate-based. The objective is to compare where each case is relatively strong or weak across BSC perspectives and not to rank the two enterprises against a common absolute benchmark. Second, as noted in Section 3.3, each SME’s performance score is normalized against its own operationally defined target and threshold

rather than against the other enterprise's figures, so differences in scale, equipment, or business age do not distort the normalized comparison. Third, using each enterprise's most recent complete two-year records, rather than forcing both cases onto an artificially identical calendar window, preserves the integrity of each case's data rather than introducing gaps or estimated values solely to achieve calendar alignment. Accordingly, the two-year period differs between cases (2024–2025 for the dry-processing case and 2023–2024 for the liquid-processing case) because each reflects the most complete records available for that enterprise at the time of data collection.

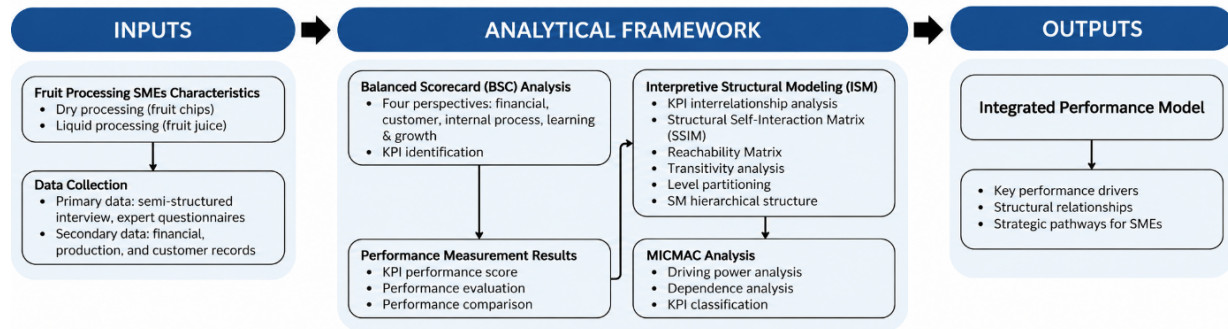


Figure 1. Research framework integrating BSC-based performance assessment with ISM–MICMAC analysis for fruit-processing SMEs

Note: BSC = balanced scorecard; ISM = interpretive structural modeling; SMEs = small and medium-sized enterprises; KPI = key performance indicator; MICMAC = cross-impact matrix multiplication applied to classification, from the French “matrice d’impacts croisés multiplication appliquée à un classement”.

Table 2. Profile of the two fruit-processing small and medium-sized enterprises (SMEs)

Characteristic	Dry-Processing SME	Liquid-Processing SME
Main product	Fruit chips	Fruit juice
Business age	31 years	22 years
Number of employees	11	17
Main processing equipment	Vacuum fryer; drying system	Cup filling and sealing equipment
Production output	7,250 kg/year	≈1,133 cartons/day (353,600 cartons/year)
Principal market(s)	Domestic market	Domestic market
Period represented by the records	2024–2025	2023–2024

3.2 Data Collection

Qualitative KPIs for BSC measurement were assessed by four respondents per case: the SME owner, the manager, a government extension officer, and a senior employee, each selected for having more than ten years of relevant experience with the enterprise or its industry, yielding a total of eight respondents across the two cases. The ISM expert panel comprised five informants: the owner of the dry-processing case (a business successor with experience spanning the enterprise's operating history), the manager and a senior employee of the liquid-processing case (both engaged with the enterprise since its founding), an academic professor specializing in agroindustry management, and a government extension officer familiar with the regional fruit-processing agroindustry. Each expert completed the SSIM covering 171 unique KPI pairs individually, supported by the research team, to clarify item wording where needed, rather than through group discussion. When the experts' individual judgments for a given pair diverged, the majority judgment was adopted as the final SSIM entry.

Data were collected through semi-structured interviews and questionnaires with SME owners, supplemented by secondary financial and production records covering a two-year period for each firm in the sample. When complete primary records were unavailable, proxy or estimated values were used. In particular, for the liquid-processing case, customer base records were only available as a count at the time of founding (2004) and a current count (2025), rather than as annual snapshots; the long-term change over this cumulative period was therefore used as a customer base growth proxy, expressed as a compound annual growth rate (CAGR), when longitudinal records of repeat purchasing by individual customers were unavailable. This limitation is discussed in Section 5.5. This proxy reflects

customer base expansion and should not be interpreted as a measure of customer retention, loyalty, or repeat-purchase behavior. Where direct waste generation records were unavailable, literature-derived waste generation ratios were used to estimate waste volume. These estimated values were explicitly distinguished from the measurements derived directly from the enterprise records.

3.3 Balanced Scorecard Development and Key Performance Indicator Measurement

The 19 KPIs were initially identified through a review of the BSC literature relevant to agroindustry and SME performance measurement and were subsequently validated with both case SME owners to confirm their relevance and applicability to each enterprise's operations. Both SMEs reported broadly similar strategic objectives centered on profitability, customer satisfaction, production efficiency, and workforce development which supported the application of a common set of KPIs across both cases for comparative purposes.

The strategic objectives for each case were translated into measurable KPIs across the four BSC perspectives (financial, customer, internal process, and learning and growth), resulting in a set of KPIs incorporating both quantitative and qualitative measures. Quantitative KPIs were derived from two years of financial and operational records for each case SME, while qualitative KPIs were assessed through structured Likert-scale interviews with the four respondents described in Section 3.2, each independently rating the indicator on a 1–5 scale, yielding a composite score with a possible range of 4–20: $IK_{\max} = PP \times R \times E_{\max} = 4 \times 1 \times 5 = 20$; $IK_{\min} = PP \times R \times E_{\min} = 4 \times 1 \times 1 = 4$. Where PP denotes the number of respondents, R denotes the number of ratings provided by each respondent, and E denotes the maximum and minimum values on the 1–5 Likert scale.

All KPIs were normalized onto a common 0–100% performance scale using one of three formulas, depending on the measurement type and optimization direction of each indicator. For quantitative KPIs, where a higher value indicates better performance (benefit-type, e.g., sales growth, production volume), performance was calculated using Eq. (1). The target values used in the normalization process were established separately for each case SME. These targets were determined based on each enterprise's operational objectives, historical performance records, and internally defined performance expectations. Therefore, the normalized scores represent the level of achievement relative to each case SME's own operational target rather than an absolute benchmark for comparing different processing industries.

$$\text{Performance} = \frac{\text{Actual}}{\text{Target}} \times 100\% \quad (1)$$

where, Actual denotes the observed value of the KPI, and Target denotes the desired performance value established for the indicator. For quantitative KPIs where a lower value indicates better performance (cost-type, e.g., defective products, production waste), an upper threshold (Max) representing the worst acceptable condition was established for each indicator, and performance was calculated using Eq. (2). The maximum acceptable thresholds were determined separately for each case SME based on their operational conditions, historical performance records, and internally defined acceptable limits. Since the two case SMEs represent different processing systems with distinct production processes, product characteristics, and quality requirements, the threshold values were not assumed to be identical across cases.

$$\text{Performance} = \frac{\text{Max} - \text{Actual}}{\text{Max} - \text{Target}} \times 100\% \quad (2)$$

where, Max denotes the worst acceptable value established for the KPI, Actual denotes the observed value, and Target denotes the desired performance value. Eq. (2) yields values below 0% when the actual performance exceeds the worst-case threshold and values above 100% when the actual performance surpasses the target, both mathematically valid outcomes that were retained and interpreted accordingly. The maximum acceptable thresholds were determined separately for each SME based on values reported directly by the SME owner during the interview, reflecting the owner's own assessment of acceptable versus unacceptable performance levels rather than an external industry benchmark. For qualitative KPIs assessed through Likert-scale interviews, performance was normalized against the maximum attainable composite score using Eq. (3).

$$\text{Performance} = \frac{\text{Composite score}}{20} \times 100\% \quad (3)$$

where, Composite score denotes the total score obtained from the four respondents on the 1–5 Likert scale, with a maximum attainable score of 20. For interpretive purposes, composite scores were additionally classified into five qualitative categories using equal-width intervals (Sturges' approach), with class width calculated as $\frac{IK_{\max} - IK_{\min}}{m} = \frac{20 - 4}{5} = 3.2$, where m is the number of categories, yielding: very poor (4.0–7.2), poor (7.3–10.4), fair (10.5–13.6), good (13.7–16.8), and very good (16.9–20.0). Perspective-level performance scores were obtained by averaging the normalized performance of all KPIs within each perspective, for each case separately, and visualized using a radar chart to compare performance balance across the two product typologies.

3.4 Interpretive Structural Modeling Procedure

Following BSC measurement, the identified KPIs were subjected to ISM to uncover their structural interdependencies. The combined expert panel described in Section 3.2 assessed the contextual relationship between each pair of KPIs (i, j) using an SSIM, employing the standard V-A-X-O notation: V (i influences j), A (j influences i), X (mutual influence), and O (no relationship). The SSIM was converted into a binary initial reachability matrix as follows.

$$a_{ij} = \begin{cases} 1, & \text{if SSIM entry is V or X} \\ 0, & \text{if SSIM entry is A or O} \end{cases}$$

$$a_{ji} = \begin{cases} 1, & \text{if SSIM entry is A or X} \\ 0, & \text{if SSIM entry is V or O} \end{cases}$$

The initial reachability matrix was then tested for transitivity. If element i reaches element j , and element j reaches element k , then i must also reach k . Entries were added to satisfy transitive relationships and were marked separately from the direct relationships originally derived from expert judgment, yielding the final reachability matrix.

Level partitioning was then performed iteratively on the final reachability matrix using Eq. (4). For each KPI i , the reachability set $R(i)$ (elements influenced by i , including i itself) and the antecedent set $A(i)$ (elements influencing i , including i itself) were derived, and their intersection computed.

$$I(i) = R(i) \cap A(i) \quad (4)$$

Elements for which $R(i) = I(i)$ were assigned to the top hierarchical level and removed from the matrix. This procedure was repeated iteratively on the remaining elements until every KPI had been assigned a level. This produced a hierarchical structure, subsequently visualized as an ISM digraph, in which lower levels represent foundational driving indicators and higher levels represent dependent outcome indicators.

3.5 Cross-Impact Matrix Multiplication Applied to Classification

The driving power (DP) and dependence power (D) of each KPI were calculated directly from the final reachability matrix using Eq. (5). For KPI i , DP_i is the row sum, representing the number of elements it influences (including itself), while D_i is the column sum, representing the number of elements that influence it.

$$DP_i = \sum_{j=1}^n a_{ij}$$

$$D_i = \sum_{j=1}^n a_{ji} \quad (5)$$

where, n is the total number of KPIs. Each KPI was subsequently plotted on a DP–D diagram and classified into one of four categories following the MICMAC method, using the mean of all DP_i and D_i values as the threshold separating high and low power:

- Autonomous (low DP, low D);
- Dependent (low DP, high D);
- Linkage (high DP, high D);
- Independent (high DP, low D).

The ISM hierarchy and MICMAC classification were subsequently used as a common structural reference for interpreting the case-specific BSC results. Lower-performing indicators from each case were mapped separately onto the hierarchy to examine their structural positions and to develop an exploratory sequence of managerial attention. This procedure does not represent a causal intervention model; rather, it provides a diagnostic interpretation of where case-specific performance weaknesses are located within the expert-perceived structure.

4 Results

4.1 Identification of Balanced Scorecard Performance Indicators

The development of performance indicators was initiated by translating the strategic objectives of fruit-processing SMEs into measurable performance indicators within the BSC framework. As illustrated in Figure 2, the strategic objectives were mapped across four BSC perspectives, namely financial, customer, internal process, and learning and growth perspectives.

The strategic mapping demonstrates that performance improvement in fruit-processing SMEs requires an integrated perspective rather than isolated measurement of individual outcomes [11, 19, 20]. While the financial

perspective reflects the final achievement of business sustainability, its realization depends on the development of customer capability, internal process effectiveness, and organizational learning. These interconnections indicate that performance indicators operate within a structured system, where foundational capabilities influence operational achievements and ultimately determine business outcomes [11]. Following the strategic alignment process, the identified performance indicators were subsequently established. A total of 19 KPIs were selected, incorporating both quantitative and qualitative indicators. The complete list of performance indicators and their classification based on the corresponding BSC perspectives is presented in Table 3.

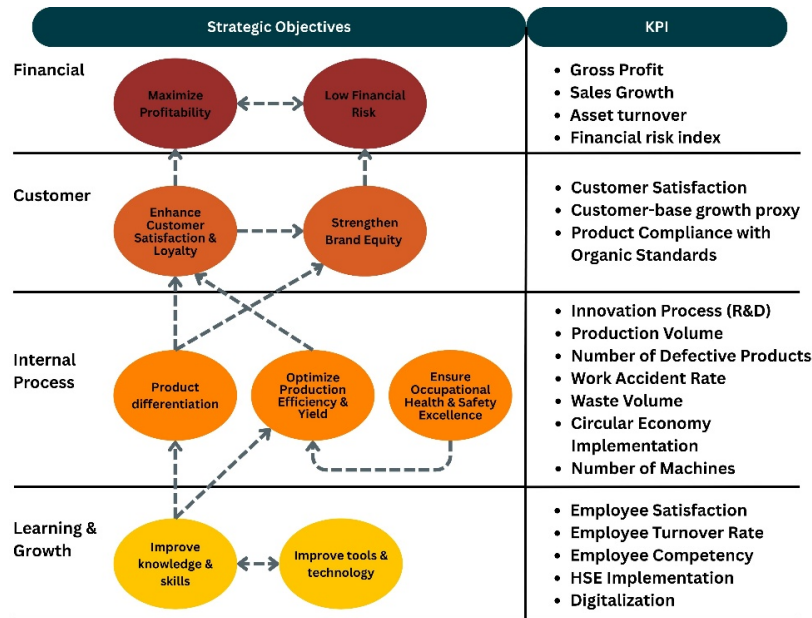


Figure 2. Strategic objectives and KPI mapping based on the BSC framework

Note: BSC = balanced scorecard; KPI = key performance indicator; R&D = research and development; HSE = health, safety, and environment.

Table 3. BSC performance indicators used in performance assessment

BSC Perspective	KPI Code	Performance Indicator	Measurement Type	Type (Benefit/Cost)
Financial	KPI1	Gross profit	Quantitative	Benefit
	KPI2	Sales growth	Quantitative	Benefit
	KPI3	Asset turnover	Quantitative	Benefit
	KPI4	Financial risk index	Qualitative	–
Customer	KPI5	Customer satisfaction	Qualitative	–
	KPI6	Customer-base growth proxy	Quantitative	Benefit
	KPI7	Product compliance with organic standards	Qualitative	–
Internal Process	KPI8	Innovation process (R&D)	Qualitative	–
	KPI9	Production volume	Quantitative	Benefit
	KPI10	Number of defective products	Quantitative	Cost
	KPI11	Work accident rate	Quantitative	Cost
	KPI12	Waste volume	Quantitative	Cost
	KPI13	Number of machines	Quantitative	Benefit
	KPI14	Circular economy implementation	Qualitative	–
Learning & Growth	KPI15	Employee satisfaction	Qualitative	–
	KPI16	Employee turnover rate	Quantitative	Cost
	KPI17	Employee competency	Quantitative	Benefit
	KPI18	HSE implementation	Qualitative	–
	KPI19	Digitalization	Qualitative	–

Note: BSC = balanced scorecard; KPI = key performance indicator; R&D = research and development; HSE = health, safety, and environment. Work accident rate (KPI11) and employee turnover rate (KPI16) are conceptually cost-type indicators; however, because their targets were set at zero, Eq. (2)—which requires a non-zero denominator (Max-Target)—is not applicable. Both indicators were therefore evaluated using Eq. (1), where achieving the zero-incident target corresponds to 100% performance; “–” indicates that the indicator does not have a direct benefit or cost orientation in the performance assessment framework.

Table 4. Operational definitions, formulas, and data sources of the balanced scorecard (BSC) performance indicators

Key Performance Indicator (KPI)	Operational Definition	Formula	Unit	Data Source	Measurement Period
KPI1	Margin between revenue and direct production cost	$\frac{NR-COGS}{S-Ret}$	%	Internal sales & cost of goods sold (COGS) records	2-year average (dry: 2024–2025; liquid: 2023–2024)
KPI2	Rate of increase in sales between periods	$\frac{(S_n-S_{n-1})}{S_{n-1}}$	%	Internal annual sales records	Same as KPI1
KPI3	Efficiency of asset use in generating revenue	$\frac{S}{TA}$	Ratio	Sales records + owner-reported asset inventory ^a	Same as KPI1
KPI4	Perceived financial instability	Likert	Score	Owner interview/questionnaire	Snapshot (single administration)
KPI5	Satisfaction with product/service	Likert	Score	Owner/manager interview	Snapshot
KPI6	Long-term expansion of the customer base ^b	Dry: $\frac{B-N}{S_t}$; Liquid: compound annual growth rate (CAGR)	%	Owner-reported customer counts	Dry: annual (2024–2025); Liquid: cumulative 2004–2025
KPI7	Conformity to organic/quality standards	Likert	Score	Owner interview	Snapshot
KPI8	Extent of new product/process development activity	Likert	Score	Owner interview	Snapshot
KPI9	Total output generated	$\sum Prod$	kg (dry)/cartons (liquid)	Dry: monthly log; Liquid: estimated ^c	Annual
KPI10	Absolute defective output per period	$\sum Def$	kg (dry)/cups (liquid)	Dry: per-batch record; Liquid: estimated ^c	Annual
KPI11	Frequency of workplace accidents relative to hours worked	$\frac{Acc}{TWH}$	%	Owner-reported incident count	Annual
KPI12	Quantity of process waste generated	$\sum Waste$	L (dry)/kg (liquid)	Estimated from raw-material ratio ^d	Annual
KPI13	Number of machines owned relative to the enterprise-defined target	$\frac{M_o}{M_t}$	%	Owner interview	Current snapshot
KPI14	Extent of resource-reuse practice	Likert	Score	Owner interview	Snapshot
KPI15	Workforce satisfaction level	Likert	Score	Owner/employee interview	Snapshot
KPI16	Rate of staff replacement	$\frac{(J-L)}{(0.5 \times (S_o+S_1))}$	%	Dry: annual record; Liquid: assumed ^e	Annual
KPI17	Proportion of workforce trained	$\frac{E_{tr}}{E_{tot}}$	%	Owner-reported training participation	Annual
KPI18	Extent of occupational health & safety practice	Likert	Score	Owner interview	Snapshot
KPI19	Extent of digital technology adoption	Likert	Score	Owner interview	Snapshot

Note: Variable definitions: NR = net revenue; S = sales; Ret = returns; TA = total assets; E = end-of-period customers; N = new customers; S_t = start-of-period customers; Acc = number of accidents; TWH = total working hours; M_o = machines owned; M_t = target machines; J = joining employees; L = leaving employees; S_o , S_1 = starting/ending headcount; E_{tr} = employees trained; E_{tot} = total employees; Likert = 4-item Likert-scale survey, composite score range 4–20 (see Section 3.3, Eq. (3)). ^aAsset value is a limited proxy (main equipment plus estimated basic tools only; excludes buildings and current assets), which likely overstates KPI3. ^bMeasurement method differs between cases due to data availability; not directly comparable as an absolute rate. ^cEstimated from reported daily volume examples annualized over working days. ^dEstimated using literature-derived waste ratios rather than direct measurements. ^eLiquid-processing case turnover is assumed to be 0% based on stable headcount since founding, not an official year-by-year record.

To support reproducibility, Table 4 presents the operational definition, computational formula, measurement unit, data source, and measurement period for each KPI. Several indicators rely on proxy measures or estimation procedures owing to data limitations inherent to SME-level record-keeping; these are flagged directly against the corresponding entries and revisited as limitations in Section 5.5.

To illustrate the normalization procedure, three worked examples are provided using the dry-processing case's 2025 data:

- Benefit-type KPI

Gross profit (KPI1): Actual = 34.2%, Target = 35.0%.

Performance = $\frac{34.2\%}{35\%} = 97.8\%$.

• Cost-type KPI

Number of defective products (KPI10): Actual = 140 kg, Target = 30 kg, Max = 100 kg.

Performance = $\frac{100-140}{100-30} \times 100\% = -\frac{40}{70} \times 100\% = -57.1\%$. The negative value indicates that actual defect output exceeded even the pre-defined worst-case threshold.

• Zero-target KPI

Work accident rate (KPI11): Actual = 0 accidents/total working hours = 0%, Target = 0%. Because both Actual and Target equal zero, direct division is undefined; by convention, achieving the zero-incident target is scored as 100% performance, consistent with the treatment described for KPI11 and KPI16 in the note beneath Table 3.

The target and max values used in all three examples were reported directly by the SME owner rather than derived from external industry benchmarks, consistent with the exploratory, case-based nature of this study.

4.2 Comparative Performance Analysis

A comprehensive performance comparison requires the integration of multiple indicators that capture both achieved outcomes and the organizational capabilities underlying those outcomes. Therefore, the identified BSC indicators were quantitatively assessed after normalization to establish a comparable performance scale between two fruit-processing product typologies, namely dry-processed products represented by fruit chips and liquid-processed products represented by fruit juice. This comparative analysis reveals the extent to which each product typology demonstrates different performance characteristics across financial, customer, internal process, and learning and growth perspectives, while also identifying variations in achievement among individual indicators. The comparative performance scores of the identified KPIs are presented in Table 5.

Table 5. Comparative performance scores of balanced scorecard (BSC) indicators

Perspective	Key Performance Indicator (KPI)	Dry-Processed Performance	Dry Range (SD)	Liquid-Processed Performance	Liquid Range (SD)
Financial	KPI1	97.8%	–	88.4%	–
	KPI2	89.5%	–	53.9%	–
	KPI3	21.0%	–	52.4%	–
	KPI4	75.0%	1 (0.50)	75.0%	1 (0.50)
Customer	KPI5	65.0%	1 (0.50)	100.0%	0 (0.00)
	KPI6	85.7%	–	5.9%	–
	KPI7	65.0%	2 (0.96)	70.0%	1 (0.58)
	KPI8	65.0%	3 (1.26)	50.0%	1 (0.58)
Internal Process	KPI9	90.6%	–	23.6%	–
	KPI10	-57.1%	–	-100.0%	–
	KPI11	100.0%	–	100.0%	–
	KPI12	36.0%	–	100.0%	–
	KPI13	86.7%	–	41.7%	–
	KPI14	75.0%	1 (0.50)	60.0%	0 (0.00)
	KPI15	75.0%	1 (0.50)	85.0%	1 (0.50)
Learning & Growth	KPI16	100.0%	–	100.0%	–
	KPI17	45.5%	–	23.5%	–
	KPI18	80.0%	3 (1.41)	70.0%	1 (0.58)
	KPI19	70.0%	1 (0.58)	70.0%	1 (0.58)

Note: SD = standard deviation. Range and SD reflect dispersion across four independent raters (1–5 Likert scale) per qualitative KPI; not applicable to KPIs derived from single-source enterprise records. “–” indicates that the range and SD were not available due to insufficient observations.

The comparative performance assessment reveals distinct performance profiles between dry-processed and liquid-processed product typologies, indicating that neither typology consistently achieves higher performance across all BSC dimensions. Dry-processed products demonstrate stronger achievement in financial and production-related indicators, whereas liquid-processed products show relatively higher performance in customer-oriented and resource utilization indicators. These differences reflect variations in performance characteristics across the two product typologies.

In the financial perspective, dry-processed products achieved higher performance in gross profit margin (97.8%) and sales growth (89.5%) compared with liquid-processed products (88.4% and 53.9%, respectively). However, liquid-processed products showed higher asset turnover performance (52.4%), indicating stronger asset utilization.

Differences were also observed in customer performance, where liquid-processed products achieved higher customer satisfaction (100.0%), while dry-processed products demonstrated stronger customer-base growth proxy score (85.7%). The internal process perspective showed notable variations, with dry-processed products exhibiting higher production volume (90.6%), performance on the number of machines (86.7%), and innovation process activity (65.0% vs. 50.0%), whereas liquid-processed products achieved better waste volume (100.0%). Meanwhile, both typologies showed comparable performance in terms of the financial risk index, workplace safety, employee turnover, and digitalization.

Following the comparative assessment at the KPI level, the performance scores of individual indicators were further consolidated into their respective BSC perspectives to develop an integrated performance profile of each product typology. The consolidation process was performed by calculating the average normalized performance score of KPIs within each perspective, allowing the overall achievement of financial, customer, internal process, and learning and growth dimensions to be evaluated. The resulting BSC perspective-level performance scores are presented in Figure 3.

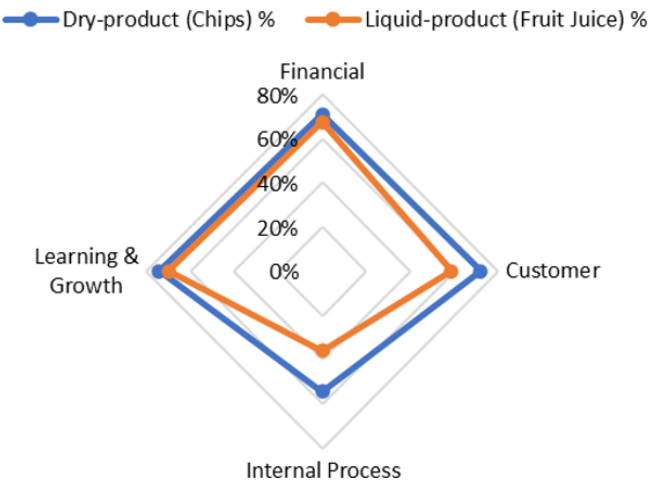


Figure 3. Balanced scorecard (BSC) performance profile of dry-processed and liquid-processed product typologies

Because KPI10 produced performance scores below 0% for both cases (dry processed: -57.1%; liquid processed: -100.0%), a sensitivity check was performed by re-computing the perspective-level and overall averages with negative scores capped at a floor of 0% (that is, $\text{Performance}' = \max(0\%, \text{Performance})$) rather than retained as computed. Under this alternative treatment, the dry-processing case's Internal Process average rose from 56.6% to 64.8%, and the liquid-processing case's rose from 39.3% to 53.6%; the overall unweighted average across all 19 KPIs rose from 66.6% to 69.6% (dry) and from 56.3% to 61.6% (liquid). In both the uncapped and capped scenarios, the dry-processing case outperformed the liquid-processing case at both the perspective and overall levels, indicating that the comparative conclusions of this study are not an artifact of retaining uncapped negative scores. Negative scores were retained as the primary reporting convention because capping would obscure the magnitude by which actual defect output exceeded the predefined worst-case threshold, which is considered diagnostically useful for the managerial implications discussed in Section 5.4.2.

4.3 Interpretive Structural Modeling Analysis

4.3.1 Structural self-interaction matrix

The first step in the ISM procedure involved constructing the SSIM, in which the combined expert panel described in Section 3.2 assessed the contextual relationship between every pair of the 19 KPIs using the V-A-X-O notation defined in Section 3.4. Table 6 presents the resulting SSIM. As the notation is directional, only the upper triangle of the matrix is populated during elicitation. The corresponding relationship in the opposite direction is subsequently derived when the SSIM is converted into the initial reachability matrix.

4.3.2 Development of initial reachability matrix

The initial reachability matrix was developed based on expert assessments to represent the direct influence relationships between indicators, where the existence of a relationship was denoted by a binary value. The resulting initial reachability matrix is presented in Table 7.

Table 6. Structural self-interaction matrix (SSIM)

Key Performance Indicator (KPI)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1		A	A	X	A	A	A	A	A	A	O	A	A	A	A	A	A	O	A
2			A	X	A	A	A	A	A	A	O	A	A	A	A	A	A	O	A
3				X	A	A	O	A	A	A	O	A	A	A	O	A	A	O	A
4					O	O	O	O	O	O	O	O	O	O	O	O	O	O	O
5						V	V	A	A	A	O	O	O	O	O	O	A	O	O
6							V	O	A	A	O	O	O	O	O	O	A	O	O
7								O	A	A	O	O	O	V	O	O	O	O	O
8									V	V	O	V	A	V	O	O	V	O	A
9										V	O	V	A	O	O	O	A	O	O
10											O	V	O	O	O	O	A	O	O
11												O	O	O	O	O	O	A	O
12													O	V	O	O	O	O	A
13														O	O	O	O	O	O
14															O	O	O	O	A
15																A	V	O	O
16																	A	O	O
17																		O	V
18																			O
19																			

Note: V indicates that indicator i influences indicator j ; A indicates that indicator j influences indicator i ; X indicates mutual influence; O indicates no relationship. Only the upper-triangular entries are shown; the lower-triangular entries are omitted.

Table 7. Initial reachability matrix of balanced scorecard (BSC) indicators

Key Performance Indicator (KPI)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
6	1	1	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
7	1	1	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0
8	1	1	1	0	1	0	0	1	1	1	0	1	0	1	0	0	1	0	0
9	1	1	1	0	1	1	1	0	1	1	0	1	0	0	0	0	0	0	0
10	1	1	1	0	1	1	1	0	0	1	0	1	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
12	1	1	1	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0
13	1	1	1	0	0	0	0	1	1	0	0	0	1	0	0	0	0	0	0
14	1	1	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
15	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0
16	1	1	1	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0
17	1	1	1	0	1	1	0	0	1	1	0	0	0	0	0	1	1	0	1
18	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0
19	1	1	1	0	0	0	0	1	0	0	0	1	0	1	0	0	0	0	1

Note: 1 indicates a direct influence relationship from the row KPI to the column KPI; 0 indicates no direct influence.

4.3.3 Final reachability matrix and level partitioning

The final reachability matrix represents both direct and transitive relationships, where a value of “1” indicates a direct relationship identified from expert judgment, while “1*” represents an indirect relationship derived through transitivity. This matrix provides the basis for subsequent level partitioning and hierarchical structure development in the ISM analysis. The final reachability matrix is presented in Table 8.

The hierarchical arrangement shows that KPI13 is positioned at the lowest level (Level 9), indicating its foundational role within the system as an underlying driver influencing higher-level indicators. The upper levels consist of indicators that represent more dependent outcomes, with KPI1, KPI2, KPI3, KPI4, and KPI11 positioned at Level 1. Meanwhile, intermediate levels represent the sequential transmission of influence among indicators, where operational, organizational, and capability-related indicators gradually contribute to higher-level performance

outcomes. The complete structural relationship among indicators is shown in the ISM digraph (Figure 4).

Table 8. Final reachability matrix

Key Performance Indicator (KPI)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	DP_i
1	1	1*	1*	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4
2	1	1	1*	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4
3	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4
4	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4
5	1	1	1	1*	1	1	1	0	0	0	0	0	0	1*	0	0	0	0	0	8
6	1	1	1	1*	0	1	1	0	0	0	0	0	0	1*	0	0	0	0	0	7
7	1	1	1*	1*	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	6
8	1	1	1	1*	1	1*	1*	1	1	1	0	1	0	1	1*	1*	1	0	1*	16
9	1	1	1	1*	1	1	1	0	1	1	0	1	0	1	0	0	0	0	0	11
10	1	1	1	1*	1	1	1	0	0	1	0	1	0	1*	0	0	0	0	0	10
11	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1
12	1	1	1	1*	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	6
13	1	1	1	1*	1*	1*	1*	1	1	1*	0	1*	1	1*	1*	1*	1*	0	1*	17
14	1	1	1	1*	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	5
15	1	1	1*	1*	1*	1*	1*	1*	1*	1*	0	1*	0	1*	1	1*	1	0	1*	16
16	1	1	1	1*	1*	1*	1*	1*	1*	1*	0	1*	0	1*	1	1	1*	0	1*	16
17	1	1	1	1*	1	1	1	1*	1	1	0	1*	0	1*	1*	1	1	0	1	16
18	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	2
19	1	1	1	1*	1*	1*	1*	1	1*	1*	0	1	0	1	1*	1*	1*	0	1	16
D_i	17	17	17	17	9	10	11	6	7	8	2	9	1	13	6	6	6	1	6	

Note: DP = driving power; D = dependence power. 1 indicates a direct influence relationship; 1* indicates an indirect relationship derived through transitivity; 0 indicates no relationship.

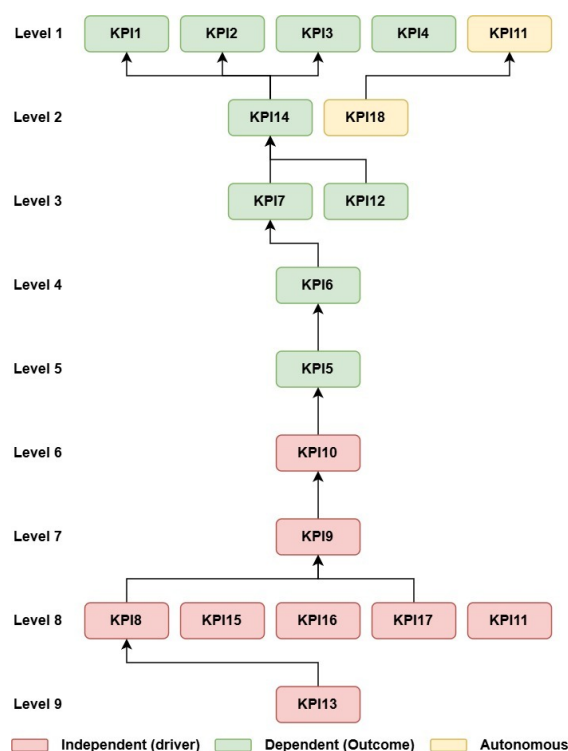


Figure 4. ISM digraph

Note: ISM = interpretive structural modeling; KPI = key performance indicator.

Of the 150 non-diagonal relationships in the final reachability matrix, 82 (54.7%) were directly asserted by the expert panel, while 68 (45.3%) were derived through transitivity closure rather than direct judgment, indicating that just over half of the structural map reflects direct expert assessment.

4.3.4 Classification of performance indicators by driving and dependence power

A total of eight indicators (KPI8, KPI9, KPI10, KPI13, KPI15, KPI16, KPI17, and KPI19) were classified as independent variables, demonstrating high DP and relatively low D. These indicators represent potential influencing factors within the system because changes in these variables may affect other performance indicators. Conversely, nine indicators (KPI1, KPI2, KPI3, KPI4, KPI5, KPI6, KPI7, KPI12, and KPI14) were identified as dependent variables, indicating that their performance is largely influenced by other factors within the structural system. Meanwhile, KPI11 and KPI18 were classified as autonomous variables due to their relatively low DP and D. These indicators exhibit limited connectivity with other indicators, suggesting that they have a relatively isolated position within the performance structure. For full reproducibility, Table 9 reports the DP and D values underlying this classification for all 19 KPIs. The spatial distribution of all indicators based on their DP and D is illustrated in the MICMAC matrix presented in Figure 5.

Table 9. Driving power (DP) and dependence power (D) values

Key Performance Indicator (KPI)	DP	D	Classification
KPI1	4	17	Dependent
KPI2	4	17	Dependent
KPI3	4	17	Dependent
KPI4	4	17	Dependent
KPI5	8	9	Dependent
KPI6	7	10	Dependent
KPI7	6	11	Dependent
KPI8	16	6	Independent
KPI9	11	7	Independent
KPI10	10	8	Independent
KPI11	1	2	Autonomous
KPI12	6	9	Dependent
KPI13	17	1	Independent
KPI14	5	13	Dependent
KPI15	16	6	Independent
KPI16	16	6	Independent
KPI17	16	6	Independent
KPI18	2	1	Autonomous
KPI19	16	6	Independent

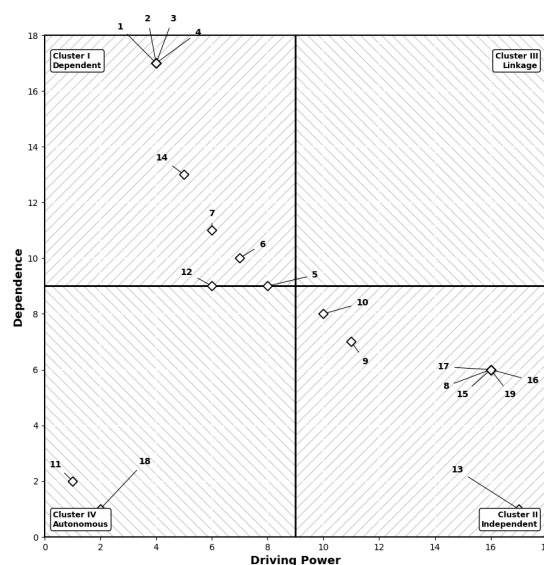


Figure 5. Classification of performance indicators using cross-impact matrix multiplication applied to classification (MICMAC)

The MICMAC matrix illustrates the distribution of performance indicators based on their DP and D characteristics. The results indicate that the system is predominantly composed of independent and dependent indicators, representing the main driving factors and performance outcomes, respectively. Independent indicators exhibit high DP and low D, indicating their potential role as influencing elements within the system, whereas dependent indicators reflect outcomes that are influenced by other indicators. Meanwhile, only a limited number of indicators are categorized as autonomous, showing relatively weak connections within the system. No linkage indicators were identified, suggesting that the performance structure is primarily characterized by a directional relationship between driving factors and dependent outcomes rather than highly interdependent relationships among indicators.

5 Discussion

5.1 Performance Variations Across Product Typologies

5.1.1 Financial perspective

Both processing cases demonstrated relatively strong financial performance, with dry-processed products achieving higher gross profit margin (97.8% vs. 88.4%) and sales growth (89.5% vs. 53.9%), while liquid-processed products showed markedly higher asset turnover (52.4% vs. 21.0%). Asset turnover is widely recognized in agribusiness financial-performance literature as a key indicator of how efficiently a firm converts its asset base into revenue [29], suggesting that the liquid-processed case utilizes its (comparatively smaller) asset base more efficiently than the dry-processed case despite its weaker profitability and sales growth, a pattern consistent with capital-intensity differences between dry-processing equipment (e.g., vacuum fryers, drying systems) and the lighter fixed-asset requirements of juice extraction and bottling. Both cases reported financial risk at the “good” but not highest category (75.0%), consistent with agri-food literature on enterprises’ shared exposure to raw-material price fluctuations and input cost volatility [30]. Because this indicator did not differentiate the two cases, it likely reflects a sector-wide vulnerability, such as fruit price seasonality, rather than a typology-specific management weakness.

5.1.2 Customer perspective

The customer perspective revealed a marked difference between the two cases. The liquid-processing case achieved higher customer satisfaction (100.0% vs. 65.0%), whereas the dry-processing case recorded a higher customer-base growth proxy score (85.7% vs. 5.9%). The latter indicator represents the change in the recorded customer base over the available observation period and should not be interpreted as actual customer retention, loyalty, or repeat-purchase behavior because longitudinal customer-level purchasing records were unavailable.

Customer acquisition, retention, and expansion represent distinct components of customer lifecycle performance and therefore should not be treated interchangeably [31]. Similarly, customer satisfaction is conceptually distinct from loyalty-related behavioral outcomes, and the strength of their relationship varies across contexts [32]. Empirical evidence also shows that organizational conditions may affect customer acquisition and retention differently, including situations in which acquisition improves while retention deteriorates [33]. Accordingly, the higher customer-base growth proxy observed in the dry-processing case cannot be interpreted as evidence of stronger customer retention or loyalty. Instead, customer-base development may reflect acquisition-oriented mechanisms in addition to existing customer relationships. New-customer acquisition can be influenced by prospecting effectiveness, conversion processes, and marketing support [34]. In SME contexts, market-sensing and customer-linking capabilities, including the strategic use of digital and social-media channels, can further support firms in identifying and engaging market opportunities [35]. Therefore, the contrasting results for customer satisfaction and customer-base growth in the two cases should be interpreted as differences between customer perception and customer-base development rather than as differences in loyalty or relationship maturity.

5.1.3 Internal process perspective

The internal process perspective showed the clearest within-case imbalance across the two processing cases. The two cases differed substantially in production volume relative to capacity, with the dry-processing case achieving 90.6% and the liquid-processing case 23.6%. However, both recorded negative performance on the number of defective products (dry-processed: -57.1%; liquid-processed: -100.0%), indicating that recorded defective output exceeded the pre-defined worst-case threshold in both cases. This is consistent with evidence that increasing production volume without proportionally scaling quality control efforts elevates the number of defective products, as heightened throughput stresses inspection and quality assurance processes [36]. Digitalized quality control and lean principles have been shown to mitigate this effect in food manufacturing contexts, suggesting that the liquid-processed case’s more severe defective-product performance may reflect quality control investment not keeping pace with production growth [37].

Performance on the number of machines also differed substantially between the two cases (dry-processed: 86.7%; liquid-processed: 41.7%). Equipment-efficiency studies using the overall equipment effectiveness framework link inadequate machine capacity to increased downtime and quality losses through overburdened machines and disrupted process flows [38], suggesting that the lower performance on the number of machines in the liquid-processing case

may be associated with its defect and downtime challenges. Both cases, by contrast, achieved full performance on workplace accident rate (100.0%). Systematic-review evidence indicates that structured occupational health and safety management systems reduce industrial accidents by 10.3% to 90%, largely independent of production capacity or throughput pressures [39], consistent with safety being governed more by procedural investment than by the capacity constraints affecting production quality. Circular economy performance was comparable across the two cases (dry-processed: 75.0%; liquid-processed: 60.0%), aligning with evidence that waste management and resource efficiency remain achievable for agri-food SMEs despite limited capital or scale, particularly through upcycling and improved process design [36]. Notably, KPI8 (dry-processing case) showed the widest inter-rater dispersion observed in this study (range = 3, standard deviation (SD) = 1.26), suggesting that the four respondents held meaningfully different perceptions of the enterprise's innovation activity, plausibly reflecting differing vantage points between ownership, operational management, and external extension roles.

5.1.4 Learning and growth perspective

Both cases exhibited comparable strengths in workforce stability, with identical full performance on employee turnover rate (100.0%) and broadly comparable employee satisfaction (dry-processed: 75.0%; liquid-processed: 85.0%). Similarly, KPI18 (dry-processing case) exhibited high dispersion (range = 3, SD = 1.41), indicating disagreement among respondents on the adequacy of occupational safety practices despite the enterprise's strong aggregate score. However, both cases recorded their weakest performance across all 19 KPIs on employee competency (dry-processed: 45.5%; liquid-processed: 23.5%). This shared weakness, despite otherwise stable and satisfied workforces, points to a structural skills gap rather than a retention problem. This is consistent with evidence that employee competencies mediate the relationship between human resource practices and organizational performance, meaning stability and satisfaction alone do not translate into performance gains without adequate underlying skill levels [40]. It also aligns with evidence showing that digital transformation benefits depend jointly on digital technology, employee digital skills, and transformation strategy, with skill levels functioning as a necessary complement rather than a byproduct of technology adoption [36]. The low competency scores have direct relevance for both cases' internal process constraints (Section 5.1.3): machine and process investments alone are unlikely to resolve the observed defect and efficiency shortfalls without parallel investment in workforce skill development. The consistently strong turnover and satisfaction performance observed in both cases, by contrast, suggests that workforce retention in these SMEs is not currently a limiting factor, leaving competency development as the more actionable priority for the learning and growth perspective.

5.2 Structural Drivers of Performance: Insights from Interpretive Structural Modeling

The ISM analysis identified number of machines (KPI13) as the sole Level 9 driver, with the highest DP of 17 and minimal D of 1 among all indicators. This result is unusually pronounced: with 19 KPIs in the system, the maximum theoretically possible DP is 19, meaning KPI13 directly or indirectly influences nearly every other indicator while itself being shaped by essentially nothing else. This concentration is broadly consistent with prior ISM applications in manufacturing and technology-adoption contexts, where capital and equipment-related factors also occupy the foundational position in the hierarchy. This concentration is broadly consistent with prior ISM applications in manufacturing and resource-constrained SME contexts, where capital and equipment-related factors also occupy the foundational position in the hierarchy. A study of sustainable procurement barriers in Indonesian food manufacturing SMEs similarly found financial constraints anchoring the entire structural system [41], and a bibliometric ISM analysis of technology implementation barriers in developing-country contexts identified cost as the single most fundamental factor among fourteen examined [42].

This concentration is explainable by the specific technological character of fruit-processing operations. Equipment such as vacuum fryers or drying units does not merely support production; it defines its physical ceiling. No improvement in employee competency, satisfaction, or digitalization can raise output beyond the ceiling set by the number of machines installed. This asymmetry is consistent with the resource-based view's distinction between resources that are merely valuable and those that are additionally rare and difficult to substitute [43]: a highly skilled workforce operating undersized equipment cannot exceed that equipment's throughput limit, whereas the reverse is not true, meaning number of machine functions as a necessary condition that the Level 8 capability indicators cannot substitute for.

The absence of any linkage-quadrant indicators admits two distinct explanations, which this study cannot fully separate. The first is substantive: fruit-processing SMEs in this study operate a single primary production line built around one central technological bottleneck, which tends to produce a tree-like directional architecture where influence flows outward from a small number of root variables, differing from systems involving multiple independent stakeholders where mutual reinforcement more commonly generates linkage-type feedback. The second is methodological: judging a bidirectional relationship (X) in the SSIM requires the expert panel to recognize reciprocal influence explicitly, a more demanding judgment than assigning a single direction of influence, and this elicitation format may itself have discouraged the reporting of mutual influence independent of whether such

reciprocity exists in the underlying system. This is best read as a limitation of the elicitation procedure rather than a claim that fruit-processing SMEs are structurally incapable of feedback dynamics.

The autonomous positioning of the two workplace safety indicators, KPI11 and KPI18, is consistent with the structural explanation above. Occupational health and safety compliance is typically driven by external regulatory requirements and fixed procedural investment rather than by the internal production logic linking equipment capacity to capability and operational outcomes, which explains their structural isolation from both the driving and dependent indicator clusters rather than merely weak connectivity to them.

5.3 Interpreting Balanced Scorecard Performance Profiles Through the Interpretive Structural Modeling Structure

Integrating the BSC and ISM findings provides a structurally informed interpretation of the performance asymmetry described in Section 5.1. The methodological integration of these frameworks combines the multi-perspective assessment capability of the BSC with the structural influence mapping capability of ISM, enabling a more comprehensive interpretation of how performance indicators are positioned within a network of structural interdependencies [44, 45]. The ISM model in this study was used exploratorily as a shared structural reference for locating case-specific performance patterns within the broader performance system.

From a resource-based perspective, differences in organizational performance may be associated with the configuration and deployment of firm-specific resources and capabilities [43]. In operations management contexts specifically, physical asset configurations and technological capacity function as foundational, lower-level resource drivers that shape the upper limits of operational and downstream financial performance [46]. The ISM hierarchy in this study operationalizes this logic empirically. It identifies the structural sequence linking foundational resource indicators with downstream financial indicators, rather than merely asserting that resources matter in the abstract.

Liquid-processed products showed comparative strength in asset turnover and customer satisfaction, positioned at Level 1 and Level 5 respectively, despite their weaker driver base. This indicates that these outcomes are not solely governed by the KPI13-anchored structural pathway. This is consistent with customer satisfaction's relatively modest DP of 8 and comparatively higher D of 9 within the MICMAC classification, meaning it is more susceptible to factors outside the core equipment-capability pathway. Customer-related outcomes provide a further example of this distinction. The liquid-processing case records higher customer satisfaction, whereas the dry-processing case shows a higher customer-base growth proxy. Previous studies indicate that customer satisfaction and loyalty-related outcomes are conceptually related but do not necessarily move in parallel, because their relationship can depend on additional relational and contextual factors [32, 47].

Overall, the integrated interpretation demonstrates the value of combining BSC and ISM without treating the ISM hierarchy as a case-specific causal model. The BSC identifies what performs relatively well or poorly in each enterprise, while the ISM provides a common expert-perceived structural reference indicating where those indicators are positioned within the hierarchy. When overlaid with the performance profile of each enterprise, this shared structure can yield different case-specific managerial implications. Thus, the contribution of the integrated framework lies not in validating or causally explaining the BSC results, but in locating performance weaknesses within the structural hierarchy and supporting a more systematic sequencing of managerial attention under resource constraints.

5.4 Implications

5.4.1 Theoretical implications

This study extends the BSC beyond its conventional role as a static, perspective-isolated measurement tool toward a structurally informed performance framework. It addresses the limitation raised in Section 2.1, where the BSC treats KPIs as independent metrics. By integrating ISM, the study shows that performance indicators in fruit-processing SMEs form a coherent nine-level structural influence hierarchy rather than existing as parallel, unrelated measures. This closes the three-way gap identified in Section 2.3 between structural interdependency modeling, multi-perspective performance measurement, and SME-level agroindustry application, offering a replicable template for future studies in resource-constrained organizational settings.

5.4.2 Managerial and practical implications

The clearest practical message for SME owners in Malang Raya is one of sequencing, not spending more money everywhere at once. The number of machines sits at the base of the hierarchy for a reason: no amount of investment in staff training, digitalization, or innovation can push output beyond what installed equipment physically allows. A manager with limited capital is better served asking "Is my machine count the bottleneck?" before asking "Should I train my staff?" or "Should I digitize my records?" This does not mean that capability-level investments are wasted. This means that their payoff is capped until the equipment constraint is addressed. For the liquid-processed case, whose number of machines (41.7% of target) trails the dry-processing case (86.7% of target), and whose defect performance is the weakest indicator observed in this study, this points to a concrete first step: conducting

a capacity and bottleneck assessment to identify the specific source of the constraint. Depending on the outcome, suitable responses may include maintenance of existing equipment, process rebalancing, equipment sharing or leasing arrangements with other producers, staff training, or, if the assessment confirms a genuine equipment shortfall, the acquisition of additional processing equipment.

Employee competency is the second lever and arguably the most overlooked. It is the single weakest KPI in both cases, despite an otherwise stable and satisfied workforce. This is not a hiring or retention problem but a training gap. For managers, this suggests that partnering with local vocational institutions or Dinas Koperasi-run skills programs is likely to be more cost-effective than general employee welfare spending, since the workforce is already stable and willing but under-skilled for the technical demands of consistent quality production.

For extension officers and cooperative institutions supporting fruit-processing SMEs across the region, the nine-level hierarchy offers something more concrete than general advice: a diagnostic sequence. Before designing a capacity-building program for a given SME, an advisor can use this hierarchy as a checklist, starting from the bottom. Is the equipment capacity adequate for the target volume? Is basic staff competency in place? Only once these foundational levels are addressed does it make sense to invest in operational-level interventions such as defect reduction training or customer relationship programs, since those indicators sit structurally downstream and are unlikely to improve in isolation.

Beyond Malang Raya, the broader lesson for fruit-processing and equipment-dependent SMEs is that not all KPIs deserve equal attention, and intuition about which ones matter most can be wrong. Customer satisfaction and retention, for instance, showed a weak structural connection to the core equipment-capability pathway in this study, meaning that improving them likely requires relationship-focused and market-facing actions rather than production-side investment, even though they appear alongside operational KPIs in a standard scorecard. Finally, the assessment approach itself, a small four-respondent Likert panel producing a simple 0–100% composite score, is deliberately low-cost and does not require external consultants or specialized software, making it a realistic diagnostic tool that resource-constrained SMEs and their local extension services can apply on their own with only modest facilitation support.

5.5 Limitations

Several limitations of this study should be considered when interpreting the findings. First, the purposive sampling of two SME cases designed to capture the region's two dominant product typologies limits the statistical generalizability of the comparative BSC findings to the broader population of fruit-processing SMEs in Malang Raya. Relatedly, because each processing type is represented by only a single enterprise, any observed performance difference between the dry- and liquid-processing cases cannot be fully disentangled from firm-specific characteristics, such as management practices, ownership history, or resource endowment unique to that particular enterprise, rather than being attributable to the processing type. Second, several indicators relied on transparent proxy estimates, including the long-term customer growth rate as a substitute for annual retention and literature-derived waste generation ratios due to incomplete longitudinal records at the enterprise level. Although documented and methodologically justified, these proxies introduce estimation uncertainty. In particular, KPI6 for the liquid-processing case was derived from a 22-year cumulative window (2004–2025) rather than the two-year window used for most other indicators, limiting its direct comparability in magnitude to period-matched KPIs and the dry-processing case's annual growth measure. Third, the ISM structural model was derived from a single combined expert panel of five experts. Although this panel was deliberately composed to reflect a consensus understanding across both cases, the resulting hierarchy remains subject to the subjectivity inherent in expert-elicited structural modeling techniques. Additionally, divergent pairwise judgments among the five ISM experts were resolved by majority rule rather than a formal reliability assessment (e.g., Kendall's W), consistent with the exploratory, small-panel nature of this study. Finally, this study was conducted within a single region (Malang Raya), and the resulting structural hierarchy and performance drivers may not be directly generalizable to fruit-processing SMEs operating under different agroecological, market or institutional conditions.

6 Conclusions

This study developed and applied an integrated BSC–ISM framework to evaluate and structurally analyze the performance of fruit-processing agroindustry SMEs in Malang Raya, Indonesia. The BSC assessment revealed that the dry-processing and liquid-processing case SMEs exhibit distinct, non-uniform performance profiles across financial, customer, internal process, and learning-and-growth perspectives. The ISM analysis further identified a nine-level structural hierarchy, in which the number of machines emerged as the most foundational structural indicator, with foundational capability indicators cascading upward through operational processes toward financial and customer outcomes, a pattern corroborated by the MICMAC classification, which identified eight independent (driving), nine dependent (outcome), and two autonomous indicators, with no linkage indicators present. By examining the BSC performance profiles in relation to this structural hierarchy, the study demonstrated that

performance differences between the two cases can be interpreted in relation to their differential strength on foundational structural indicators, offering an integrative explanation beyond what either method could provide independently. These findings extend the BSC literature and provide managers with an evidence-based basis for strengthening customer-related performance outcomes, including customer satisfaction and customer-base development indicators. Future research may extend this framework across a broader sample of fruit-processing SMEs and additional regions and may build upon these structural findings by incorporating strategy formulation using fuzzy strengths, weaknesses, opportunities, and threats analysis combined with the analytic hierarchy process, and risk analysis using failure mode and effects analysis combined with artificial neural networks to translate the identified performance drivers into actionable, risk-informed development strategies.

Author Contributions

Conceptualization, I.S., I.W., N.M.L., R.I., and D.P.A.; methodology, I.S., R.A.H., M.F.F.M., and D.P.A.; software, I.W. and N.M.L.; validation, I.S., R.A.H., M.F.F.M., and D.P.A.; formal analysis, I.W., N.M.L., and R.I.; investigation, I.W., N.M.L., and R.I.; resources, I.S., R.A.H., and M.F.F.M.; data curation, I.W., N.M.L., and R.I.; writing—original draft preparation, I.W., N.M.L., and R.I.; writing—review and editing, I.S., R.A.H., M.F.F.M., and D.P.A.; visualization, I.W., N.M.L., and R.I.; supervision, I.S., R.A.H., M.F.F.M., and D.P.A.; project administration, I.S.; funding acquisition, I.S. All authors have read and agreed to the published version of the manuscript.

Funding

This research was funded by the Indonesian Endowment Fund for Education (LPDP) on behalf of the Indonesian Ministry of Higher Education, Science and Technology through the Riset Kolaborasi Indonesia (RKI) program, supported by the Dana Abadi Perguruan Tinggi (DAPT) fund (Grant No.: 02134.3/UN10.A0501/B/KS/2025).

Informed Consent Statement

All participants voluntarily participated in this study. Before data collection, the purpose of the research, procedures involved, and intended use of the collected information were explained to all respondents. Informed consent was obtained from participants before conducting interviews and questionnaire assessments. The identities of respondents and participating SMEs were kept confidential.

Ethical Approval

This study involved interviews, questionnaire assessments, and expert judgments related to organizational performance evaluation without experimental intervention. The study was conducted in accordance with applicable ethical standards and was approved by the Research Ethics Committee, Faculty of Agricultural Technology, Universitas Brawijaya (approval no. 05968/DST/UN10.F1001/B/PT/2026; date of approval: September 17, 2026), as part of the broader research project from which this manuscript is one of several outputs. Confidentiality procedures were applied to protect respondents and enterprise identities.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Acknowledgements

The authors would like to express their gratitude to the fruit processing businesses in the Malang Raya area, East Java, Indonesia, for their support, including the information and assistance they provided during field observations, interviews, and data collection. The authors also express their gratitude for the institutional and technical support received during the preparation of this study.

Conflicts of Interest

The authors declare no conflicts of interest.

Declaration on the Use of Generative AI and AI-assisted Technologies

The grammatical structure and the coherence of sentences in this article were improved and paraphrased by using QuillBot AI. The authors have manually rechecked the accuracy and correctness of all generated sentences to ensure they align with the research topic and empirical data. The final manuscript was reviewed by an English language expert from the Faculty of Agroindustrial Technology and Biosystem, Universitas Brawijaya to improve language quality while maintaining the original meaning. The authors remain fully responsible and accountable for the entire content of this article.

References

- [1] M. M. Urugo, E. Yohannis, T. A. Teka, H. F. Gemede, Y. B. Tola, S. F. Forsido, A. Tessema, M. Suraj, and J. Abdu, "Addressing post-harvest losses through agro-processing for sustainable development in Ethiopia," *J. Agric. Food Res.*, vol. 18, 2024. <https://doi.org/10.1016/j.jafr.2024.101316>
- [2] D. Utonga, C. S. Tundui, and E. Mkuna, "Harnessing performance through digital technology adoption: An empirical analysis of SMEs in the Tanzanian fruit juice processing industry," *Cogent Bus. Manag.*, vol. 13, no. 1, p. 2612771, 2026. <https://doi.org/10.1080/23311975.2026.2612771>
- [3] I. Santoso, I. Wafi'uddin, N. M. Lu'ayya, A. Choirun, M. Purnomo, and A. A. Sulianto, "An integrated performance assessment method for SMEs fruit processing sustainability in Indonesia," *Cogent Eng.*, vol. 11, no. 1, p. 2374941, 2024. <https://doi.org/10.1080/23311916.2024.2374941>
- [4] S. Sengupta, S. Choudhary, R. Obayi, and R. Nayak, "Reducing food loss through sustainable business models and agricultural innovation systems," *Supply Chain Manag.*, vol. 29, no. 3, pp. 540–572, 2024. <https://doi.org/10.1108/SCM-01-2023-0059>
- [5] F. Facchini, B. Silvestri, S. Digiesi, and A. Lucchese, "Agri-food loss and waste management: Win-win strategies for edible discarded fruits and vegetables sustainable reuse," *Innov. Food Sci. Emerg. Technol.*, vol. 83, p. 103235, 2023. <https://doi.org/10.1016/j.ifset.2022.103235>
- [6] M. Crossland, R. Coe, C. Lamanna, B. Chiputwa, L. Orero, B. Adoyo, S. Kumar, V. M. Mwangi, E. Anyango, L. E. Fuchs *et al.*, "Measuring the holistic performance of food and agricultural systems: A systematic review," *Front. Sustain. Food Syst.*, vol. 9, p. 1472109, 2025. <https://doi.org/10.3389/fsufs.2025.1472109>
- [7] M. I. de Carvalho, S. Relvas, and A. P. Barbosa-Póvoa, "A roadmap for sustainability performance assessment in the context of agri-food supply chain," *Sustain. Prod. Consum.*, vol. 34, pp. 565–585, 2022. <https://doi.org/10.1016/j.spc.2022.10.001>
- [8] M. I. Hendri, "Performance management in SMEs: Integrating bibliometric insights and systematic review on antecedents and outcomes," *Soc. Sci. Humanit. Open*, vol. 12, p. 102205, 2025. <https://doi.org/10.1016/j.ssaho.2025.102205>
- [9] M. Constantin, J. Sapena, A. Apetrei, and S. R. Pătărlăgeanu, "Deliver smart, not more! Building economically sustainable competitiveness on the ground of high agri-food trade specialization in the EU," *Foods*, vol. 12, no. 2, p. 232, 2023. <https://doi.org/10.3390/foods12020232>
- [10] J. A. Restrepo-Morales, E. A. Giraldo-Betancur, D. A. López-Cadavid, M. M. Grados-Vásquez, and L. W. Olórtiga-Cóndor, "Enhanced organizational performance: Integrating dimensions for sustainable growth," *Sustainability*, vol. 15, no. 21, p. 15186, 2023. <https://doi.org/10.3390/su152115186>
- [11] R. S. Kaplan and D. P. Norton, "The balanced scorecard: Measures that drive performance," *Harv. Bus. Rev.*, vol. 70, pp. 71–79, 1992.
- [12] Y. K. Liao, S. Wang, V. T. Thinh, and W. Y. Wu, "An investigation of leading and lagging indicators for balanced scorecard: A meta-analytic approach," *SAGE Open*, vol. 15, no. 4, p. 21582440251359833, 2025. <https://doi.org/10.1177/21582440251359833>
- [13] A. S. Ayswer, N. Ramasamy, M. DevAnand, and N. Santhi, "Analysing the performance indicators in SME using ISM-MICMAC approach," *J. Inst. Eng. India Ser. C*, vol. 105, no. 5, pp. 987–996, 2024. <https://doi.org/10.1007/s40032-024-01110-7>
- [14] M. Ertuğrul and E. Özdarak, "Measuring airline performance: An integrated balanced scorecard-based MEREC-CoCoSo model," *Sustainability*, vol. 17, no. 13, p. 5826, 2025. <https://doi.org/10.3390/su17135826>
- [15] J. N. Warfield, "Developing interconnection matrices in structural modeling," *IEEE Trans. Syst. Man Cybern.*, vol. SMC-4, no. 1, pp. 81–87, 1974. <https://doi.org/10.1109/TSMC.1974.5408524>
- [16] F. Amer, S. Hammoud, H. Khatatbeh, S. Lohner, I. Boncz, and D. Endrei, "The deployment of balanced scorecard in health care organizations: Is it beneficial? a systematic review," *BMC Health Serv. Res.*, vol. 22, no. 1, p. 65, 2022. <https://doi.org/10.1186/s12913-021-07452-7>
- [17] R. E. Brimelow, A. Amalathas, E. Beattie, G. Byrne, and N. N. Dissanayaka, "The use of balanced scorecards in mental health services: An integrative review and thematic analysis," *J. Behav. Health Serv. Res.*, vol. 50, no. 1, pp. 128–146, 2023. <https://doi.org/10.1007/s11414-022-09806-3>
- [18] F. Akanga, "The use of the balanced scorecard by SMEs in Francophone Africa: An empirical investigation," *Account. Res. J.*, vol. 39, no. 2, pp. 305–321, 2025. <https://doi.org/10.1108/ARJ-04-2024-0151>
- [19] M. B. Tudose, V. D. Rusu, and S. Avasilcai, "Financial performance—Determinants and interdependencies between measurement indicators," *Bus. Manag. Econ. Eng.*, vol. 20, no. 1, pp. 119–138, 2022. <https://doi.org/10.3846/bmee.2022.16732>
- [20] S. Moores, N. Sayed, C. Lento, and G. Wakil, "Leveraging the balanced scorecard to reformulate the strategy of a performing arts theater: A stakeholders' perspective," *J. Appl. Account. Res.*, vol. 24, no. 1, pp. 47–69,

2022. <https://doi.org/10.1108/JAAR-11-2021-0308>

- [21] J. H. Dahooie, N. Mohammadi, I. Meidutė-Kavaliauskienė, and A. Binkytė-Velienė, “A novel performance evaluation framework for new service development in the healthcare industry using hybrid ISM and ANP,” *Technol. Econ. Dev. Econ.*, vol. 27, no. 6, pp. 1481–1508, 2021. <https://doi.org/10.3846/tede.2021.15699>
- [22] Rico, R. Darma, D. Salman, and Mahyuddin, “The performance of Arabica coffee agribusiness actors in North Toraja Regency, Indonesia,” *Cogent Food Agric.*, vol. 10, no. 1, 2024. <https://doi.org/10.1080/23311932.2024.2363002>
- [23] M. Yani, Machfud, M. Asrol, E. Hambali, P. Papilo, S. Mursidah, and M. Marimin, “An adaptive fuzzy multi-criteria model for sustainability assessment of sugarcane agroindustry supply chain,” *IEEE Access*, vol. 10, pp. 5497–5517, 2022. <https://doi.org/10.1109/ACCESS.2022.3140519>
- [24] N. de Sena Silva, S. C. Gomes, E. J. M. Arruda Filho, and S. V. R. Galina, “Sustainability orientation, environmental knowledge integration, and strength of ties: Governance and sustainable performance in regulated agribusiness,” *Corp. Soc. Responsib. Environ. Manag.*, vol. 32, no. 6, pp. 7310–7325, 2025. <https://doi.org/10.1002/csr.70080>
- [25] E. Ramos, P. S. Coles, M. Chavez, and B. Hazen, “Measuring agri-food supply chain performance: Insights from the Peruvian kiwicha industry,” *Benchmarking*, vol. 29, no. 5, pp. 1484–1512, 2022. <https://doi.org/10.1108/BIJ-10-2020-0544>
- [26] M. Kumar, M. Sharma, R. D. Raut, S. K. Mangla, and V. K. Choubey, “Performance assessment of circular driven sustainable agri-food supply chain towards achieving sustainable consumption and production,” *J. Clean. Prod.*, vol. 372, p. 133698, 2022. <https://doi.org/10.1016/j.jclepro.2022.133698>
- [27] B. Axmann and H. Harmoko, “The assessment model of robotic process automation (RPA) project using benefit study and balanced scorecard (BSC) approach,” *Tech. J.*, vol. 18, no. 2, pp. 246–253, 2024. <https://doi.org/10.31803/tg-20240416111054>
- [28] M. Najib, A. A. A. Rahman, A. Abror, R. Rachmawati, M. Simanjuntak, P. Prasetya, D. Suhartanto, and F. Fahma, “Leaders’ support of sustainable innovation and business sustainability in developing countries: Evidence from small and medium food processing enterprises,” *Sustainability*, vol. 13, no. 23, p. 13091, 2021. <https://doi.org/10.3390/su132313091>
- [29] A. L. Katchova and S. J. Enlow, “Financial performance of publicly-traded agribusinesses,” *Agric. Finance Rev.*, vol. 73, no. 1, pp. 58–73, 2013. <https://doi.org/10.1108/00021461311321311>
- [30] C. A. Wolf and J. Karszes, “Financial risk and resiliency on US dairy farms: Measures, thresholds, and management implications,” *J. Dairy Sci.*, vol. 106, no. 5, pp. 3301–3311, 2023. <https://doi.org/10.3168/jds.2022-22711>
- [31] K. Matsuoka, “A framework for variance analysis of customer equity based on a Markov chain model,” *J. Bus. Res.*, vol. 129, pp. 57–69, 2021. <https://doi.org/10.1016/j.jbusres.2021.02.039>
- [32] V. Mittal, K. Han, C. Frennea, M. Blut, M. Shaik, N. Bosukonda, and S. Sridhar, “Customer satisfaction, loyalty behaviors, and firm financial performance: What 40 years of research tells us,” *Mark. Lett.*, vol. 34, no. 2, pp. 171–187, 2023. <https://doi.org/10.1007/s11002-023-09671-w>
- [33] F. F. Gu, F. F. Leung, D. T. Wang, and Y. Tang, “Navigating the double-edged sword: Executive hubris and its impact on customer acquisition and retention,” *Int. J. Res. Mark.*, vol. 41, no. 2, pp. 362–382, 2024. <https://doi.org/10.1016/j.ijresmar.2023.12.002>
- [34] S. Gopalakrishna, A. T. Crecelius, and A. Patil, “Hunting for new customers: Assessing the drivers of effective salesperson prospecting and conversion,” *J. Bus. Res.*, vol. 149, pp. 916–926, 2022. <https://doi.org/10.1016/j.jbusres.2022.05.008>
- [35] G. Cao and J. Weerawardena, “Strategic use of social media in marketing and financial performance: The B2B SME context,” *Ind. Mark. Manag.*, vol. 111, pp. 41–54, 2023. <https://doi.org/10.1016/j.indmarman.2023.03.007>
- [36] X. Teng, Z. Wu, and F. Yang, “Research on the relationship between digital transformation and performance of SMEs,” *Sustainability*, vol. 14, no. 10, p. 6012, 2022. <https://doi.org/10.3390/su14106012>
- [37] A. Hassoun, S. Jagtap, H. Trollman, G. Garcia-Garcia, N. A. Abdullah, G. Goksen, F. Bader, F. Ozogul, F. J. Barba, J. Crobotova *et al.*, “Food processing 4.0: Current and future developments spurred by the fourth industrial revolution,” *Food Control*, vol. 145, p. 109507, 2023. <https://doi.org/10.1016/j.foodcont.2022.109507>
- [38] T. Fu, S. Liu, and P. Li, “Digital twin-driven smelting process management method for converter steelmaking,” *J. Intell. Manuf.*, vol. 36, no. 4, pp. 2749–2765, 2025. <https://doi.org/10.1007/s10845-024-02366-7>
- [39] P. R. Burgess, F. T. Sunmola, and S. Wertheim-Heck, “A review of supply chain quality management practices in sustainable food networks,” *Heliyon*, vol. 9, no. 11, p. e21179, 2023. <https://doi.org/10.1016/j.heliyon.2023.e21179>
- [40] F. N. K. Otoo, “Human resource management (HRM) practices and organizational performance: The mediating role of employee competencies,” *Empl. Relat.*, vol. 41, no. 5, pp. 949–970, 2019. <https://doi.org/10.1108/ER-0>

- [41] I. Masudin, I. D. Lestari, A. Khoidir, and D. P. Restuputri, "Sustainable procurement barriers in Indonesian food manufacturing SMEs: An ISM-fuzzy MICMAC analysis," *Logistics*, vol. 9, no. 4, p. 175, 2025. <https://doi.org/10.3390/logistics9040175>
- [42] G. E. Takyi-Annan and H. Zhang, "A bibliometric analysis of building information modelling implementation barriers in the developing world using an interpretive structural modelling approach," *Heliyon*, vol. 9, no. 8, p. e18601, 2023. <https://doi.org/10.1016/j.heliyon.2023.e18601>
- [43] J. Barney, "Firm resources and sustained competitive advantage," *J. Manage.*, vol. 17, no. 1, pp. 99–120, 1991. <https://doi.org/10.1177/014920639101700108>
- [44] S. Nazari-Shirkouhi, S. Mousakhani, M. Tavakoli, M. R. Dalvand, J. Šaparauskas, and J. Antuchevičienė, "Importance-performance analysis based balanced scorecard for performance evaluation in higher education institutions: An integrated fuzzy approach," *J. Bus. Econ. Manag.*, vol. 21, no. 3, pp. 647–678, 2020. <https://doi.org/10.3846/jbem.2020.11940>
- [45] A. Tizroo, A. Esmaeili, E. Khaksar, J. Šaparauskas, and M. M. Mozaffari, "Proposing an agile strategy for a steel industry supply chain through the integration of balance scorecard and Interpretive Structural Modeling," *J. Bus. Econ. Manag.*, vol. 18, no. 2, pp. 288–308, 2017. <https://doi.org/10.3846/16111699.2017.1279683>
- [46] M. A. Hitt, K. Xu, and C. M. Carnes, "Resource based theory in operations management research," *J. Oper. Manag.*, vol. 41, pp. 77–94, 2016. <https://doi.org/10.1016/j.jom.2015.11.002>
- [47] Y. Tian and Q. Kamran, "A review of antecedents and effects of loyalty on food retailers toward sustainability," *Sustainability*, vol. 13, no. 23, p. 13419, 2021. <https://doi.org/10.3390/su132313419>