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Production Efficiency and Business Performance in Bangladesh's Agro-Processing Industry: The Role of Technology Adoption, Waste Reduction and Supply Chain Integration

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Abstract

Agro-processing companies in Bangladesh face inconsistent raw-material quality, process losses, limited technology adoption and fragmented supply chains. This conceptual framework paper develops a resource-conversion explanation linking technology adoption, waste reduction and supply chain integration to production efficiency and, consequently, business performance. Rather than conducting a pooled firm-level causal test, it examines the framework through a descriptive reanalysis of separately published secondary statistics. The Bangladesh Agro-Processors Association (BAPA) baseline covers 50 businesses, while the Bangladesh Institute of Development Studies' Skills for Employment Investment Project (BIDS-SEIP) survey reports 117 plants employing 41,546 people. In the BAPA baseline, adoption rates were 36% for TQM, 20% for JIT, 14% for HACCP, 4% for ISO and 2% for advanced 5S/Kaizen/Lean practices. The ratio of mean daily output to mean operating hours was 1.473 metric tons per hour, although these aggregate statistics cannot establish firm-level productivity. Large enterprises accounted for 38.5% of factories and 81.5% of employment in the BIDS-SEIP sample. These descriptive patterns indicate differences in capability adoption and enterprise scale; they do not test the proposed relationships. The six propositions identify potentially complementary mechanisms for future firm-level testing. A seventh proposition is anchored in the paper's own descriptives. It proposes firm size as a moderator of capability conversion. This links the historical aggregates to the future test agenda. The paper's practical contribution is a staged operations-management approach linking process measurement, loss reduction, supplier coordination and selective digital investment to business outcomes. It also identifies the measurement requirements and limitations relevant to future empirical validation.

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1. Introduction

Bangladesh's agro-processing industry connects agricultural production with manufacturing, domestic food markets and export trade. The agriculture and food-processing industry accounts for approximately 1.7% of GDP, 13% of total manufacturing production value and 6.5% of the manufacturing labour force (International Trade Administration [ITA], 2026). Bangladesh has more than 1,000 food processors and 250 exporters, while processed-food exports reached USD 341.73 million in FY 2023–2024 (Bangladesh Investment Development Authority [BIDA], n.d.). These indicators demonstrate the sector's economic role and the importance of improving production efficiency, product quality and supply-chain coordination. Agro-processing transforms variable agricultural inputs into standardized products and market value, but production is vulnerable to raw-material variation, spoilage, downtime, quality rejection and fragmented sourcing. In Bangladesh, the managerial challenge extends beyond purchasing machinery: processors must coordinate quality, information, labour, capacity and working capital to achieve consistent saleable output. The historical BAPA baseline indicates low diffusion of formal operating practices, whereas the BIDS-SEIP sector survey indicates substantial differences in enterprise size and workforce skills (Bangladesh Agro-Processors Association [BAPA], n.d.; Bangladesh Institute of Development Studies [BIDS], 2021). Recent studies in Bangladesh also point to technological capability and information exchange as drivers of adoption (Rashed et al., 2025), food-safety control deficiencies among cereal-processing SMEs (Singha et al., 2025) and the importance of supplier relationships and information quality to agro-food organizational performance (Siju et al., 2024). These studies motivate an operations-management explanation of how available resources are converted into reliable output and financial performance.

The specific research gap addressed in this paper is the absence of an integrated Bangladesh-focused framework linking technology adoption (TA), waste reduction (WR) and supply chain integration (SCI) to business performance (BP) through production efficiency (PE). Rashed et al. (2025) examine technological capability, information sharing and technology adoption in 16 Bangladesh food-processing factories, without jointly assessing waste-reduction capability, supplier/customer integration and measured conversion efficiency. Emon and Ahmed (2025) examine technology-mediated green supply-chain relationships in 243 responses from Bangladesh's agro-processing and food sector, but their model does not establish whether production efficiency mediates the entire technology-waste-integration bundle. Zhao et al. (2021) study integration, product quality and financial performance of Chinese processors, rather than the proposed three-capability structure in Bangladesh. Recent studies of Bangladeshi supply chains emphasize coordination and digitalization (Choudhury et al., 2024; Khan & Emon, 2025a, 2025b; Shareef et al., 2025), but do not test the integrated model presented here. Accordingly, the contribution is a focused, theoretically grounded synthesis and managerial diagnostic, rather than a new causal finding about capability–performance relationships. We propose the following operational conversion linkage between technology adoption (TA), waste reduction (WR), supply chain integration (SCI) and business performance (BP): production efficiency. The resource-based view (RBV) and dynamic-capabilities theory explain the deployment of firm capabilities, the natural-resource-based view (NRBV) explains loss avoidance, and the relational view explains value creation across firm boundaries (Barney, 1991; Dyer & Singh, 1998; Hart, 1995; Teece et al., 1997). The framework integrates these lenses by defining complementarity: information creates value when managers can use it to reduce losses and coordinate suppliers. This is a hypothesis for future testing, not a finding established by the available aggregate data. The paper addresses the following questions: what patterns of historical capability and scale are apparent in the available agro-processing statistics of Bangladesh; how can previous technology, waste and supply-chain results be structured around production efficiency; and what are the implications and future tests? The paper makes three contributions: (a) a transparent descriptive reanalysis of two non-combinable secondary sources; (b) an integrated, production-efficiency-based resource-conversion model; and (c) an actionable sequencing and measurement logic for operations managers. A fourth contribution is a data-

anchored size-moderation proposition. It connects the historical Bangladeshi aggregates to the testable agenda. A fifth contribution is a reproducible template for secondary analysis.
It records inconsistencies rather than suppressing them. The paper does not estimate the six proposed paths, pool coefficients or infer causal effects from aggregate evidence.

2. Literature Review and Bangladesh Agro-Processing Context

2.1 Production variability, perishability and conversion loss

Agro-processing differs from discrete manufacturing because raw materials are biological, heterogeneous and often perishable. Moisture content, maturity, contamination, size, varietal characteristics and seasonality affect process settings and achievable yield. The same plant may therefore face large differences in conversion efficiency even when machine capacity is unchanged. Yadav et al. (2022) identify perishability, food safety, traceability, demand uncertainty and network design as major agri-food supply-chain challenges. Zhao et al. (2021) also emphasize that quality and safety depend not only on the focal processor but also on coordination among supply-chain partners. Variability can enter the plant before the production process begins when processors source raw materials from numerous small producers and intermediaries in Bangladesh. Raw-material variability can lead to sorting, rework, spoilage and delayed production; shortages and poorly timed deliveries can raise idle time, emergency sourcing and inventory costs. Quality failures can then reduce first-pass yield, saleable throughput and customer reliability. Thus, production efficiency depends on both plant-level discipline and external input coordination, rather than machinery utilization alone (Yadav et al., 2022; Choudhury et al., 2024).

2.2 Technology adoption and process-control capability

Information delays can be reduced through digital production records, sensors, process controls and integrated planning, which can help maintain more consistent quality and scheduling. The advantages of Industry 4.0 depend on skills, funding, the quality of data and implementation capacity (Chauhan et al., 2021; Romanello & Veglio, 2022). Rashed et al. (2025) find that advanced-technology adoption is positively related to technological capability and information sharing in sampled Bangladesh food-processing factories. Jerin et al. (2024) provide a conceptual discussion of next-level technology-adoption intention among Bangladesh food-and-beverage SMEs, highlighting the importance of adoption readiness rather than claiming measured performance improvements. Technology ownership should therefore be distinguished from effective organizational use. The framework keeps that distinction by defining TA narrowly. TA covers monitoring, automation, control, planning and traceability. BAPA's TQM, JIT, HACCP, ISO and 5S items measure something else. They measure formal operating-practice adoption, which informs WR. This separation refines prior Bangladesh studies. Those studies often treat practice adoption and technology as one thing. The split is needed to test P6 as complementarity, not conflation. Rashed et al. (2025) report that 74% of the sampled factories were at startup-to-intermediate levels of adoption. More broadly, Khan and Emon (2025a, 2025b) report manufacturing-sector relationships among digital integration, supply-chain visibility, responsiveness and performance. These investigations substantiate a plausible information-to-decision pathway, but their cross-sector evidence cannot be considered a quantified effect in the BAPA or BIDS-SEIP samples.

2.3 Fragmented supply chains and the factory-boundary problem

A processor may stabilize production yet still receive inconsistent volumes, unclear input specifications and unreliable demand information. Supply chain integration (SCI) links procurement, production and sales within the company and links them to suppliers and customers (Flynn et al., 2010). Zhao et al. (2021) report relationships between integration, product quality and financial performance among Chinese agro-food processors. In Bangladesh, Siju et al. (2024) find that supplier partnerships, customer relationships and information quality are associated with organizational performance, although information sharing itself was not significantly associated with the outcomes examined. Shareef et al. (2025) identify information

gaps and intermediary-related inefficiencies in the agricultural supply chains in Bangladesh. These findings suggest that the quality and utilization of coordination should be considered instead of merely the volume of information shared. A standalone digital-factory investment can be of limited value if upstream quality and delivery are not stable. On the other hand, greater external information flow can be of little consequence unless the processor quantifies the conversion losses and responds to exceptions. Choudhury et al. (2024) demonstrate the significance of trade-offs between distribution and aggregation in the Bangladeshi fruit and vegetable chains. The current framework thus puts SCI alongside internal monitoring and loss prevention while the magnitude of any interaction remains to be estimated.

2.4 Integrated literature synthesis and unresolved questions

Across the three streams, recent studies examine distinct relationships using different samples, constructs and outcome measures. Technology research focuses on adoption readiness and digital-performance pathways (Jerin et al., 2024; Khan & Emon, 2025a; Rashed et al., 2025); food-quality and waste research focuses on controls, prevention and environmental practice (Emon & Ahmed, 2025; Singha et al., 2025); and supply-chain work focuses on supplier/customer relationships and market coordination (Choudhury et al., 2024; Rashid et al., 2024; Siju et al., 2024; Shareef et al., 2025). None of these studies provides a common Bangladesh firm-level dataset with matched measures of TA, WR, SCI, PE and BP. The unresolved question is whether production efficiency acts as a proximal conversion mechanism and whether jointly developed capabilities generate complementary rather than merely additive gains. Table 1 identifies the constructs and associates them with a specific operating mechanism.

Table 1: Integrated constructs and expected resource-conversion mechanisms

Construct	Operational meaning	Expected mechanism
Technology adoption (TA)	Digital monitoring, automation, process control, integrated planning and traceability.	Reduces information latency and process variance; raises control precision and asset utilization.
Waste reduction (WR)	Systematic prevention of material loss, defects, rework, waiting, energy loss, downtime and avoidable disposal.	Raises yield, lowers unit resource use and stabilizes flow.
Supply chain integration (SCI)	Internal, supplier and customer process/information integration.	Reduces raw-material, quality, delivery and demand variability before it becomes plant loss.
Production efficiency (PE)	Conversion of material, labor, energy and equipment capacity into conforming saleable output.	Proximal mediator translating capabilities into cost, quality, throughput and reliability.
Business performance (BP)	Profitability, sales growth, competitiveness, export readiness and customer performance.	Economic capture of operational gains.

Source: *authors' synthesis based on Barney (1991), Hart (1995), Flynn et al. (2010), Zhao et al. (2021) and the agro-processing literature.*
Note: *P7 adds firm size as a moderator of the TA, WR and SCI paths. It is motivated by the size-class evidence in Table 4. It is not estimated in this paper.*

3. Integrated Theoretical Framework and Propositions

3.1 Resource-based and dynamic-capability logic

The resource-based view (RBV) explains why firm-specific organizational capabilities can create advantages beyond those obtained through ownership of widely available equipment (Barney, 1991). When combined with reliable data, process knowledge, maintenance and managerial action, digital monitoring and automation can become valuable capabilities. In the case of Bangladesh agro-processing, the difference is important since the technological capability and information sharing are linked to the adoption, whereas machine purchase is not a sign of improved conversion efficiency (Rashed et al., 2025; Jerin et al., 2024). Dynamic-capabilities theory introduces sensing, seizing and reconfiguration of changing environments (Teece et al.,

1997). Agro-processing involves seasonal inputs and changing quality and demand conditions, making these routines relevant: digital information can expose problems, but production teams must re-plan, adjust processes and coordinate partners before operational performance can improve. The suggested association with PE is prospective.

3.2 Natural-resource-based view and lean loss prevention

Natural-resource-based view (NRBV) approaches the problem of waste prevention as a form of environmental stewardship and resource productivity (Hart, 1995). For agro-processors, avoidable material, water and energy losses, rework and downtime represent resources for which the firm has already paid; reducing them can improve yield and lower unit costs. A recent study on food-safety in Bangladesh also suggests that formal preventive control practices cannot be presumed to be mature among SMEs (Singha et al., 2025). Lean studies suggest that coordinated routines can be more effective than isolated tools in some manufacturing settings (Cua et al., 2001; Shah & Ward, 2003, 2007). Research on food processing identifies implementation barriers and links process discipline with operational performance (Dora et al., 2013, 2016). In this context, WR refers to the systematic measurement and prevention of defects, spoilage, waiting, rework, energy loss, unnecessary downtime and unnecessary material loss. This differs from end-of-pipe recycling. Digital measurement can be used to supplement WR to show where losses are taking place. In a food-manufacturing case study, Jagtap and Rahimifard (2019) found that food waste decreased following the installation of an IoT monitoring strategy; this is a context-specific finding, not a result size that would be anticipated of Bangladeshi processors. Aramyan et al. (2021) also emphasize the importance of innovation as a way of minimizing food-chain waste in situations where incentives and costs are harmonized.

3.3 Relational view and supply chain integration

The relational view attributes competitive value to coordinated interorganizational resources and relationships (Dyer & Singh, 1998). For agro-processors, suppliers, transporters and customers are the key to consistent grades of raw materials, delivery windows and downstream specifications. Supplier collaboration and information quality have been linked to agro-food performance in Bangladesh (Siju et al., 2024), providing context for SCI as a cross-boundary capability. SCI integrates internal, supplier and customer integration (Flynn et al., 2010). Empirical studies relate integration configurations to performance, but the results differ depending on the situation (Ataseven & Nair, 2017; Zhao et al., 2021). Agricultural-chain studies in Bangladesh explain the coordination issues and how information-enabled market connections can help (Choudhury et al., 2024; Shareef et al., 2025). The proposed argument is that external coordination can reduce variability before it becomes an internal production loss.

3.4 Production efficiency as the conversion mechanism

The relational view, NRBV and RBV emphasize interorganizational relationships, resource preservation and firm-specific resources, respectively. Each lens alone lacks an account of how capabilities become outcomes. The framework's key move is to name production efficiency as that link. TA supplies information and control over the process. WR turns that information into material and time savings. SCI stabilizes input quality and demand signals. This layered logic is the paper's main conceptual contribution. It differs from parallel-predictor models in prior Bangladesh work. The framework adds a direct conversion sequence: TA supplies information and control, WR routines improve material and time conversion, and SCI deals with the timing and quality of resources in and out of the plant. PE is proposed as the proximal outcome linking these capabilities with profitability, growth and competitiveness. It is a model-driven combination of prior theory, rather than evidence of a novel mediating effect. PE should be operationalized in future with similar product-family measures, such as material yield, first-pass quality, process loss, throughput, downtime and energy or labor intensity. Figure 1 summarizes the proposed framework and its six original paths. Valid comparisons require equivalent quantities of input, operating time and product mix; increased output does not create increased efficiency. Appendix A shows objective KPI definitions.

3.5 Complementarity and propositions for future evaluation

Complementarity implies that the marginal value of one capability increases as another capability becomes more developed. Process data can reveal downtime, but they will not necessarily reduce it unless a plant also has standard-work and root-cause routines; lean practices can enhance flow and monitoring can facilitate easier maintenance of the improvements. Tortorella and Fettermann (2018) report associations between Industry 4.0 and lean implementation, but they do not test the specific interaction proposed for Bangladesh's agro-processing industry. The propositions P1-P6 below are hypothetical assumptions; none of them is tested with the secondary aggregates in this paper. Shared supplier specifications and demand signals may allow SCI to complement process monitoring and loss-prevention routines, helping firms avoid losses before they occur. Thus, the framework proposes an information-control layer (TA), a loss-prevention layer (WR) and a coordination layer (SCI). Matched firm-level data are needed to estimate the relative contributions, interactions and business outcomes associated with these capabilities.

3.6 Proposition Development

Technology adoption and production efficiency

Prior research suggests that digital technologies can support production efficiency by improving process visibility, automation, scheduling and quality control. Studies of Industry 4.0 adoption identify workforce skills, data quality and implementation capacity as important conditions for operational gains (Chauhan et al., 2021; Romanello & Veglio, 2022). Rashed et al. (2025) report positive relationships among technological capability, information sharing and advanced-technology adoption in Bangladeshi food-processing factories. However, their findings do not directly establish a TA–PE relationship using objective production-efficiency measures. The expected association therefore depends on effective implementation and the use of technology in day-to-day process decisions.

P1. *Technology adoption is expected to be positively associated with production efficiency, conditional on implementation capability.*

Waste reduction and production efficiency

Lean and quality-management research indicates that coordinated operating practices, including TQM, JIT and TPM, are associated with manufacturing performance (Cua et al., 2001; Shah & Ward, 2003, 2007). Food-processing studies also identify implementation factors and operational outcomes associated with lean practices (Dora et al., 2013, 2016). Digital monitoring can help identify and reduce food waste (Jagtap & Rahimifard, 2019), while supply-chain innovation may reduce food waste when incentives and costs are aligned (Aramyan et al., 2021). Bangladesh research also identifies gaps in preventive food-safety controls among cereal-based SMEs (Singha et al., 2025). This literature supports the expectation that systematic prevention of defects, spoilage, rework and downtime can improve material yield and throughput, although the WR–PE relationship has not been estimated in the BAPA or BIDS-SEIP data used here.

P2. *Waste-reduction capability is expected to be positively associated with production efficiency.*

Supply chain integration and production efficiency

SCI coordinates internal functions and external partners, potentially stabilizing input quality, delivery timing and demand information. Flynn et al. (2010) examine integration–performance relationships, while Ataseven and Nair (2017) synthesize evidence showing that these relationships depend on context and configuration. Zhao et al. (2021) report links between integration, product quality and financial performance in Chinese agro-food processors. Bangladesh studies also highlight supplier partnerships, information quality and supply-chain coordination (Choudhury et al., 2024; Shareef et al., 2025; Siju et al., 2024). Collectively, this literature supports a pathway in which integration reduces variability that might otherwise create rework, idle time or waste, although it does not directly test SCI–PE in the present samples.

P3. *Supply chain integration is expected to be positively associated with production efficiency.*

Production efficiency and business performance

Efficient conversion of materials, labour, energy and equipment into conforming saleable output can lower unit costs, improve delivery reliability and strengthen customer outcomes. Studies of lean implementation link coordinated operational practices with manufacturing performance (Cua et al., 2001; Dora et al., 2013), while Incekara (2022) examines the relationship between resource-efficiency practices and production-cost performance among manufacturing SMEs. Zhao et al. (2021) find that product quality provides a pathway from integration to financial performance in Chinese agro-food processors. These findings provide related support for PE as an operational precursor to BP, but do not directly test the PE–BP association in the Bangladesh secondary sources analyzed here.
P4. *Production efficiency is expected to be positively associated with business performance.*

Production efficiency as a mediating mechanism
The framework proposes that TA, WR and SCI may influence BP partly by improving the conversion of inputs into saleable output. Related studies have tested mediation mechanisms involving technology adoption and operational performance (Emon & Ahmed, 2025) and product quality and financial performance (Zhao et al., 2021). These findings suggest that operational outcomes can transmit the effects of upstream practices to business results. However, neither study tests the specific role of PE as a mediator between the combined TA–WR–SCI capability set and BP in Bangladesh. The proposed mediation therefore requires matched firm-level measures and formal indirect-effect testing.
P5. *Production efficiency is proposed to mediate the associations of TA, WR and SCI with business performance.*

Complementarity among technology adoption, waste reduction and supply chain integration.
The benefits of individual capabilities may depend on the presence of supporting practices. Digital monitoring can identify downtime or quality problems, but the information may not lead to improvement unless waste-reduction routines support corrective action. Similarly, internal process improvements may be undermined by inconsistent supplier deliveries or unreliable customer-demand information. Research on combined Industry 4.0 and lean production provides a basis for considering the joint implementation of digital and process capabilities (Tortorella & Fettermann, 2018), while Cua et al. (2001) examine bundles of TQM, JIT and TPM practices. This evidence supports the theoretical possibility of complementarity, but the three-way interaction among TA, WR and SCI has not been directly tested in Bangladesh's agro-processing industry.
P6. *The TA-WR-SCI bundle may produce positive complementary interactions beyond the sum of its individual associations.*

One further proposition is motivated by the paper's own descriptive data. The BIDS-SEIP survey reports that large firms account for 38.5% of establishments but 81.5% of employment, indicating that the workforce is concentrated in a few large plants. The BAPA baseline adds a second signal: only 16% of surveyed firms reported formal institutional finance, suggesting that smaller processors face a real absorption constraint. Together, these patterns motivate a size-moderation proposition:
P7. *Firm size moderates the TA-PE, WR-PE and SCI-PE associations, such that the conversion return to adoption is expected to be larger in establishments with sufficient managerial and financial capacity.*

The expectation covers all three paths for different reasons. TA is capital-intensive and depends on finance and technical skills. WR and SCI need less capital but more managerial depth and coordination. Size therefore proxies a bundle of complementary capabilities, not a single resource. P7 differs from P1–P6 in two ways. It is anchored in the paper's own descriptives rather than prior literature alone, and it links the historical aggregates to the firm-level tests in Appendix B, where size stratification is already a safeguard. Size offers the clearest contrast in the available data; subsector, exports and location remain for future stratification.

P7 is a boundary condition on P1–P3, not a competing explanation. Its interplay with P5 and P6 is left to future tests.

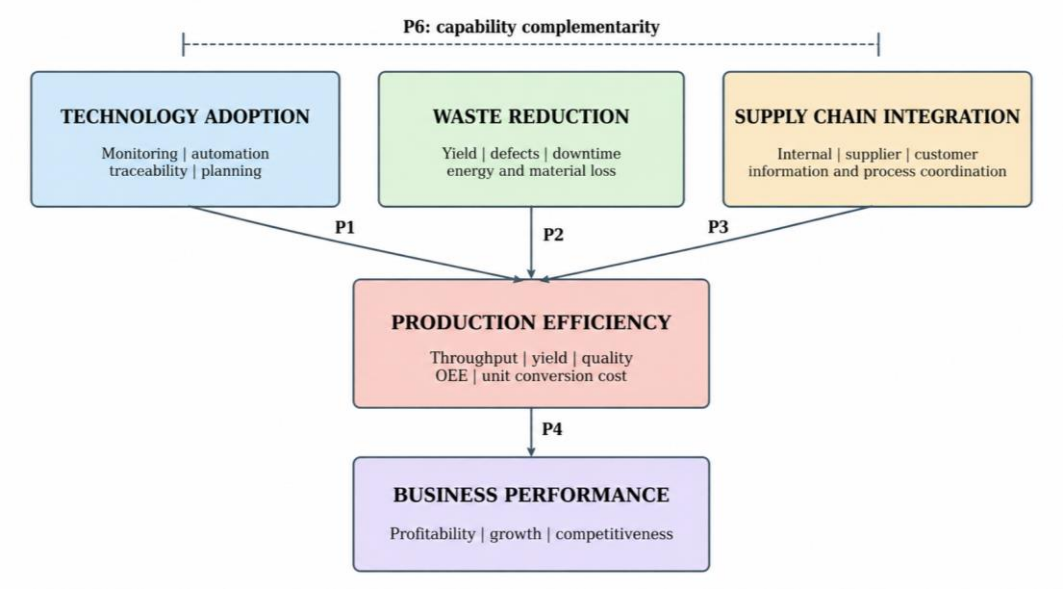


Figure 1: Proposed resource-conversion framework.
Note: P7 (not shown) proposes firm size as a moderator of P1-P3. The dashed P6 arrow denotes capability complementarity.

4. Data and Methods

4.1 Conceptual design, secondary sources and evidence boundaries

Table 2: Data sources, samples and analytic role

Source	Sample	Variables used	Analysis	Role
BAPA baseline survey	50 agro-processing MSMEs; four regional clusters	Productivity tools, production time/output, finance, HACCP/ISO, wastewater, sourcing	Wilson CIs; exact binomial diagnostics; throughput derivation	Historical capability baseline
BIDS-SEIP Skill Survey 2020-2021	117 factories; 547 employee respondents; 41,546 employees in sampled enterprises	Enterprise size, employment, output, export, skill constraints	Shares, ratios, size-class employment HHI	Sector structure and business exposure
Rashed et al. (2025)	16 Bangladesh food-processing factories	Tech capability, information sharing, adoption, performance, growth	PLS-SEM path coefficients	Recent Bangladesh technology mechanism
Emon & Ahmed (2025)	243 Bangladesh agro-processing/food responses	Green technology adoption, waste/supply practices, operational performance	PLS-SEM direct/indirect effects	Technology/ waste/collaboration mechanism
Zhao et al. (2021)	162 agro-food processors, China	Internal/supplier/customer integration, product quality, financial performance	SEM, mediation	External agro-food SCI benchmark
Incekara (2022)	2,055 manufacturing SMEs, Europe/USA	Process reengineering, waste management, production cost performance	Binary logistic regression	External resource-efficiency benchmark

Source: *BAPA; BIDS-SEIP; and cited peer-reviewed studies. Published coefficients are not statistically pooled.*

The article is a conceptual framework paper with original descriptive computations of published, source-level summary statistics; it is not a pooled-data or causal empirical test. Two sources of historical Bangladesh data are re-examined separately: a BAPA baseline of 50 agro-processors in four regional clusters, and a BIDS-SEIP skills survey of 117 agro-food factories with 547 worker respondents and 41,546 employees represented in enterprise books (BAPA, n.d.; BIDS, 2021). A third layer is published peer-reviewed firm-level studies, which are only used to determine the plausibility of proposed mechanisms. Records and published coefficients are not pooled because the sampling frames, years, variable definitions and denominators differ. The original contribution of the paper is construct integration rather than the estimation of new relationships among TA, WR, SCI, PE and BP. BAPA offers a historical snapshot of operational capabilities, including quality and productivity tools, operating time, sourcing, production and waste treatment. The BIDS-SEIP report gives establishment size, employment, output, exports and constraints of skills. The two sources are limited to their respective samples and timeframes; neither of them provides firm-level measurements of the five suggested constructs. Recent published studies are informative of theory but cannot confirm P1-P6 in these samples. Table 2 summarizes the sources, samples, variables and analytic roles used in this paper.

4.2 Transparent descriptive and concentration measures

Reported BAPA averages are converted into a transparent throughput measure. Let Qd denote average daily production and Hd denote average operating hours per day. Hourly throughput is:

$$q_h = \frac{Q_d}{H_d} = \frac{16.5}{11.2} = 1.473 \text{ MT h}^{-1} \quad (1)$$

Equation (1) divides the BAPA-reported mean daily production (16.5 metric tons) by mean daily operating time (11.2 h). The resulting value of 1.473 metric tons per hour is a ratio of means, not the mean of enterprise-specific rates. A mechanical annualization using 271 reported working days does not reconcile with the separately reported aggregate production of 29,039 metric tons; the difference is approximately a factor of 7.70. Since reporting periods and denominators may differ, this discrepancy is recorded as a consistency warning; no annual capacity-utilization claim is made. For the BIDS-SEIP size-class comparison, e_k is the share of sampled employment and f_k is the share of sampled enterprises in class k. Employment and establishment HHIs summarize concentration in the four reported size classes; these are not product-market measures. The dissimilarity index, location quotients, normalized entropy and grouped Gini are additional descriptive diagnostics rather than causal or firm-level estimates. Their numerical results and definitions appear in Table 5.

$$\text{HHI}_E = \sum_{k=1}^{K} e_k^2 = 0.6844, \qquad \text{HHI}_F = \sum_{k=1}^{K} f_k^2 = 0.2796 \quad (2)$$

These are size-class concentration diagnostics, not product-market concentration measures.

The ratio of employment to establishment HHI is 2.448, indicating a more concentrated distribution of employment than of firm counts across the four classes. The dissimilarity index summarizes this difference in distributions (Table 5).

$$D_{FE} = \frac{1}{2}\sum_{k=1}^{K} |e_k - f_k| = 0.4302 \quad (3)$$

4.3 Sample-based adoption diagnostics

In the 50 establishments in the BAPA survey, the reported proportions of capabilities are supplemented by Wilson 95% confidence intervals and one-sided exact binomial tests against a 50% reference. The eight exploratory comparisons are adjusted using the Holm procedure; Cohen's h summarizes standardized differences (Cohen, 1988). The threshold is an illustrative within-sample reference, not an industry or policy target. The sampling design restricts any interpretation to the surveyed firms.

$$\mathrm{CI}_W = \frac{\hat{p} + \frac{z^2}{2n} \pm z\sqrt{\frac{\hat{p}(1-\hat{p})}{n} + \frac{z^2}{4n^2}}}{1 + \frac{z^2}{n}} \quad (4)$$

$$p_{\text{exact}} = \sum_{r=0}^{x} \binom{n}{r} p_0^r (1-p_0)^{n-r} \quad (5)$$

$$h = 2\left[\arcsin\sqrt{\hat{p}} - \arcsin\sqrt{p_0}\right] \quad (5a)$$

4.4 Triangulation, reporting rules and limitations

Joint TA, WR, SCI, PE and BP measurements, matched firm records or a common covariance structure are not reported in the source reports. Thus, they do not permit estimation of structural paths, interaction effects, mediation or a stochastic frontier of the proposed model. P1-P6 are propositions that are not tested. Published structural coefficients by Rashed et al. (2025), Emon and Ahmed (2025) and Zhao et al. (2021) are not statistically pooled; they are context-specific support for the proposed mechanisms, not estimates of the current study. Reproducibility: all reported numerical findings are drawn from published sources or calculated directly from published counts, means and totals. No artificial microdata are generated or imputed. Where the percentages directly correspond to the counts out of 50, the exact tests are based on the integer counts prior to rounding. This reporting discipline is itself a contribution. Secondary reanalyses in this literature rarely report Wilson intervals. Few report Holm-adjusted exact tests on integer counts. None reconcile incompatible denominators in the source data. The annualization gap is recorded, not suppressed (§4.2, §5.5). All money ratios are labeled arithmetic, not efficiency, estimates. The result is a replicable template for cautious secondary analysis. P7 is motivated by size-class shares, not estimated here. The results in Table 3 are exploratory comparisons against a specified reference that are adjusted by Holm, and do not validate the proposed capability framework.

5. Quantitative Results

5.1 Productivity-tool, quality-system and waste-management readiness

Table 3: BAPA capability indicators with Wilson uncertainty and majority-adoption diagnostics

Indicator	x/n (rate)	Wilson 95% CI	Exact p	Holm p	|Cohen h|
TQM	18/50 (36%)	24.1-49.9%	0.03245	0.03245	0.284
JIT	10/50 (20%)	11.2-33.0%	1.19e-5	2.39e-5	0.644
3S	2/50 (4%)	1.1-13.5%	1.13e-12	6.80e-12	1.168
5S/Kaizen/Lean	1/50 (2%)	0.4-10.5%	4.53e-14	3.62e-13	1.287
HACCP	7/50 (14%)	7.0-26.2%	1.05e-7	4.20e-7	0.804
ISO	2/50 (4%)	1.1-13.5%	1.13e-12	6.80e-12	1.168
Wastewater treatment	1/50 (2%)	0.4-10.5%	4.53e-14	3.62e-13	1.287
Bank/financial-institution finance	8/50 (16%)	8.3-28.5%	5.82e-7	1.75e-6	0.748

Source: *authors' calculations based on Bangladesh Agro-Processors Association (n.d.). Exact p values compare sample proportions with 0.50; Holm p values adjust eight exploratory comparisons. Cohen's h expresses a standardized sample difference, not an industry benchmark.*

The historical BAPA sample suggests limited adoption of formal process and assurance routines: TQM 18/50 (36%), JIT 10/50 (20%), 3S 2/50 (4%), 5S/Kaizen/Lean 1/50 (2%), HACCP 7/50 (14%), ISO 2/50 (4%), wastewater treatment 1/50 (2%) and formal institutional finance 8/50 (16%). Wilson uncertainty and exploratory majority-reference tests are reported in Table 3. For TQM, the 95% Wilson interval is 24.1%–49.9%, with its upper bound just below the illustrative

50% reference. These rates characterize the historical sample, rather than the situation in the country in 2026 (BAPA) Table 3 reports the same indicators with Wilson intervals and exploratory majority-adoption tests. Figure 2 displays the same adoption rates with Wilson intervals.

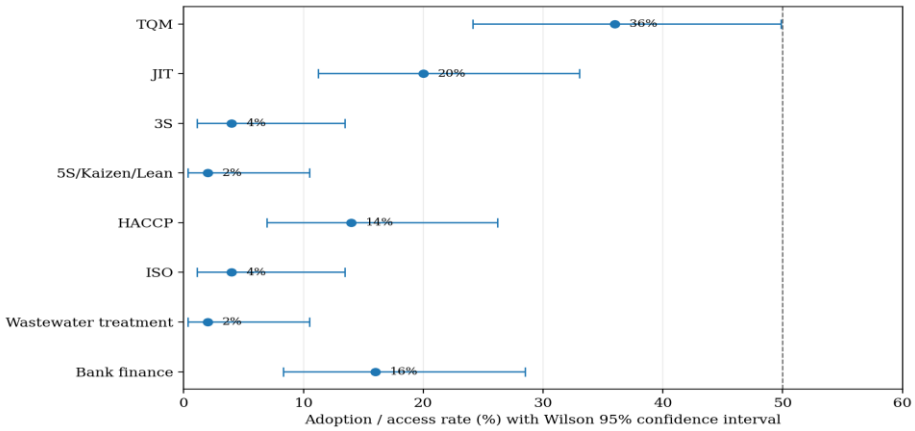


Figure 2: *Operational-system adoption and access rates in the BAPA 50-enterprise baseline, with Wilson 95% confidence intervals. The dashed line is a diagnostic 50% majority benchmark, not an industry standard.*

Source: *authors' calculations from BAPA data.*

5.2 Production-time intensity and loss exposure

BAPA reports mean daily output of 16.5 metric tons, mean daily operating time of 11.2 hours and 271 operating days per year. Dividing mean daily output by mean daily operating time gives 1.473 metric tons per hour. The source also reports that 46% of respondents were unfamiliar with productivity tools and key informants estimated fruit and vegetable handling and transport losses at 20–40%. The loss estimate is related to upstream handling and transport, not measured processing-line scrap, and thus the two should not be added to an efficiency rate (BAPA, n.d.). Reported sourcing was split among suppliers (27%), employees (46%) and mixed sourcing (27%). These are the classes of sourcing arrangements, rather than the measured impacts of SCI. These categories nevertheless demonstrate why supplier-quality procedures and traceability can be applicable to additional field studies (BAPA, n.d.; Siju et al., 2024).

5.3 Enterprise-size concentration and diffusion capacity

Table 4: BIDS-SEIP enterprise structure and employment concentration

Size class	Firms	Firm share (%)	Employment	Employment share (%)	Workers/firm
Large	45	38.5	33,854	81.5	752.3
Medium	28	23.9	5,673	13.7	202.6
Small	27	23.1	1,697	4.1	62.9
Micro	17	14.5	322	0.8	18.9
Total	117	100.0	41,546	100.0	355.1

Source: *authors' calculations from Bangladesh Institute of Development Studies (2021), surveyed establishments and employee totals.*

The BIDS-SEIP sample consists of 117 establishments: 45 large, 28 medium, 27 small and 17 micro. The large category accounts for 38.5% of firms and 33,854 of 41,546 employees (81.5%). Mean employment was approximately 752 in large, 203 in medium, 63 in small and 19 in micro establishments. Table 4 reports the size-class structure and employment concentration. The four-class employment HHI of the sample is 0.6844; it is a size-class description, not market

concentration or a national population estimate (BIDS, 2021). Figure 3 compares enterprise share with employment share across the four classes.

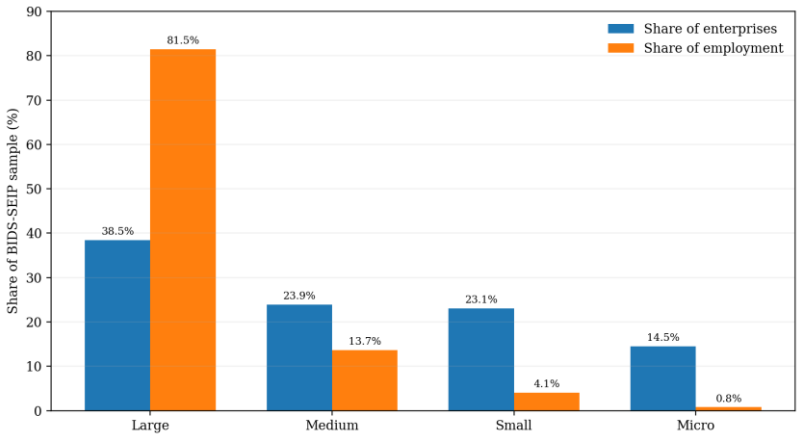


Figure 3: *Enterprise share versus employment share in the BIDS-SEIP agro-food processing sample.*
Source: *authors' calculations from BIDS-Skill Survey 2020-2021.*

The employment HHI (0.6844) is approximately 2.448 times the firm-share HHI (0.2796) and the dissimilarity between employment and establishment shares (0.4302). These diagnostics have not been reported for this sector before. Their novelty is practical, not econometric. Counting firms makes the sector look dispersed. Counting workers makes it look concentrated in a few plants. The 2.448 ratio makes that policy difference explicit. It quantifies a distinction that has stayed implicit until now. The large firm location quotient is 2.119; medium, small and micro firms are 0.571, 0.177 and 0.053 respectively (Table 5). Figure 4 presents the grouped Lorenz approximation for these size classes. This size structure has implications for policy targeting. Programs assessed by the number of workers reached can give preference to large enterprises and programs assessed by the number of firms may miss capacity concentrated in the largest group. Future primary-data research should therefore stratify by firm size and determine whether the hypothesized capability relationships vary by class.

Table 5: Derived concentration, inequality and business-exposure diagnostics

Diagnostic	Formula / basis	Value	Interpretation
Employment HHI	Σe_k^2	0.6844	Employment is highly concentrated in the large-firm class.
Firm-share HHI	Σf_k^2	0.2796	Establishment counts are more dispersed across size classes.
HHI amplification	HHI_E / HHI_F	2.448	Employment concentration is 2.45 times establishment concentration.
Dissimilarity index	$0.5\ \Sigma\lvert e_k-f_k\rvert$	0.4302	43.0% distributional separation between employment and firm shares.
Employment LQ: large	e_k/f_k	2.119	Large firms carry over twice the employment share implied by their firm share.
Employment LQ: medium	e_k/f_k	0.571	Employment is under-represented relative to establishment share.
Employment LQ: small	e_k/f_k	0.177	Strong under-representation of employment relative to establishment share.
Employment LQ: micro	e_k/f_k	0.053	Very low employment share relative to establishment share.
Grouped Gini	Class-mean Lorenz area	0.4741	Grouped approximation; within-class firm dispersion is unobserved.
Normalized employment entropy	$-\Sigma e \ln(e)/\ln(4)$	0.4379	Confirms substantial size-class concentration.

Diagnostic	Formula / basis	Value	Interpretation
Export intensity	59.86 / 2,348.47	0.02549 (2.55%)	Exports are small relative to reported full-sample output.
Output per worker	2,348.47m / 41,546	BDT 56,527	Exactly reconciles the BIDS report's stated worker productivity.
Capital per worker	261.05m / 41,546	BDT 6,283	Exactly reconciles the report's stated capital-labor figure.
Output/capital ratio	2,348.47 / 261.05	8.996	Arithmetic ratio only; not interpreted as TFP or a causal efficiency estimate.

Source: *authors' calculations from Bangladesh Institute of Development Studies (2021). The grouped Gini assumes equal employment within each size class; money ratios and output/worker indicators are arithmetic diagnostics, not causal efficiency estimates.*

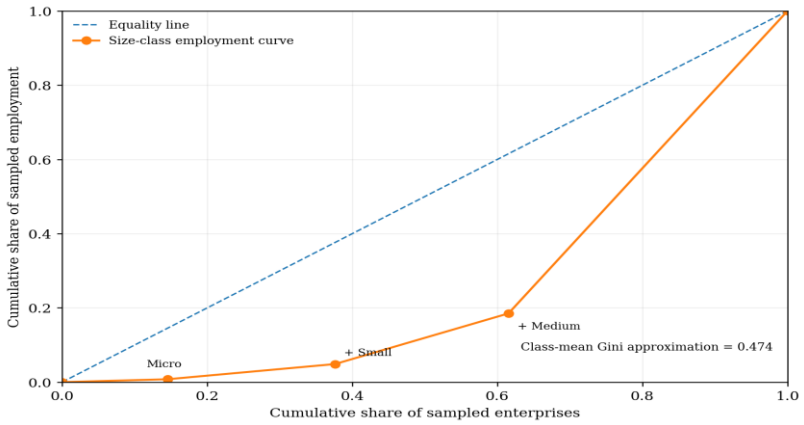


Figure 4: *Grouped Lorenz approximation for employment concentration across BIDS-SEIP enterprise-size classes.*
Source: *authors' calculations from BIDS-SEIP aggregate counts; within-class dispersion is not observed.*

5.4 Output, export intensity and skills-related business exposure

The BIDS-SEIP report records 2019 output of BDT 2,348.47 million, exports of BDT 59.86 million and capital stock of BDT 261.05 million. The monetary amounts are treated as full-sample totals because this interpretation is consistent with the report's worker-normalized statistics: output per worker of approximately BDT 56,527 and capital per worker of BDT 6,283. On this basis, exports represented 2.55% of output. These are arithmetic consistency checks and sample descriptions, rather than novel causal or total-factor-productivity estimates (BIDS, 2021).

$$I_X = \frac{59.86}{2348.47} = 0.02549 \approx 2.55\% \quad (6)$$

The BIDS-SEIP report identifies the following consequences of hard-to-fill vacancies: lost business or orders to competitors (59.62%), slowed product/service development (56.73%), and inability to meet quality standards (51.92%). These are skills-related constraints, not measured effects of TA, WR or SCI, and indicate that workforce capability should be considered in future tests of the framework (BIDS, 2021).

5.5 Robustness, multiplicity and source-consistency checks

Three checks help guard against overinterpretation. First, the BAPA exploratory tests compare observed rates of adoption with a given 50% reference, but they do not provide representative national adoption estimates. Second, the daily-output, operating-day and annual-total aggregates of the source have no demonstrably compatible denominators; their incompatibility is not a quantifiable capacity deficiency. Third, BIDS monetary aggregates are interpreted using the arithmetic approach that best reconciles published worker-normalized data. All checks are data-interpretation limits, not validation of P1-P6.

5.6 Triangulation with recent structural evidence

The proposed mechanisms receive contextual support from published firm-level studies. In a study of 16 Bangladeshi food-processing factories, Rashed et al. (2025) report significant technological capability-information sharing-adoption and adoption-performance and growth paths. Emon and Ahmed (2025) examine 243 responses from Bangladesh's agro-processing and food sector and report positive relationships involving technology adoption, waste management and supplier collaboration. Table 6 lists chosen coefficients as given by those sources; they are not re-estimated or pooled here. In China, Zhao et al. (2021) identify links among integration, product quality and financial performance in 162 agro-food processors; Incekara (2022) evaluates resource-efficiency practices and cost performance among manufacturing SMEs. These studies provide context for the proposed mechanisms. Their coefficients should not be interpreted as evidence for P1–P6 in Bangladesh.

Table 6: Peer-reviewed quantitative evidence used for mechanism triangulation

Study	Sample	Method	Key result	Framework link
Rashed et al. (2025)	Bangladesh food processing; n=16	PLS-SEM	Tech capability -> adoption β=.372, p=.049; information sharing -> adoption β=.463, p=.009; adoption -> performance β=.464, p=.001; adoption -> growth β=.521, p=.021	TA / information / BP
Emon & Ahmed (2025)	Bangladesh agro-processing/food; n=243	PLS-SEM	TAGP -> OP β=.43, t=4.33, p<.001; EFP -> OP β=.39; SEC -> TAGP β=.42; WME -> TAGP β=.24; GP -> TAGP β=.22; R^2(OP)=.93	TA / WR / supplier collaboration / OP
Zhao et al. (2021)	China agro-food processors; n=162	SEM	Internal and supplier integration -> product quality significant; quality fully mediates to financial performance; R^2(FP)=.260	SCI / quality / FP
Incekara (2022)	Manufacturing SMEs; n=2,055	Binary logistic regression	Process-reengineering model χ^2(51)=181.279, p<.001; waste-management model χ^2(51)=245.203, p<.001; Nagelkerke R^2(process)=.233	WR / process redesign / cost performance

Source: *cited peer-reviewed articles. Coefficients are reported for triangulation, not combined meta-analytically.*

6. Discussion

6.1 Technology adoption as a proposed process-control capability

Technology can influence production in terms of visibility, automation, synchronization and learning: information indicates losses, routines of control stabilize processes, planning connects capacity to supply and analysis aids corrective action. Bangladesh food-processing evidence relates technological capability and information exchange to adoption (Rashed et al., 2025), and more general manufacturing evidence to digital integration and visibility to supply-chain performance (Khan & Emon, 2025a, 2025b). These studies are consistent with the proposed mechanism; they do not prove that technology increased PE in the BAPA or BIDS-SEIP samples.

The framework also warns against the digitalization of unstable processes. Monitoring may be less actionable when master data are inconsistent or standard work is weak. P6 treats TA–WR complementarity as a hypothesis that requires matched firm-level data and explicit estimation of interaction effects (Tortorella & Fettermann, 2018).

6.2 Waste prevention as a proposed production-efficiency capability

Waste prevention can enhance the transformation of purchased inputs into saleable products by reducing material losses, defects, rework, unnecessary downtime and energy intensity. Delays can erode product value; therefore, early detection and corrective action are important in perishable operations. Related evidence comes from coordinated lean practices (Cua et al., 2001; Dora et al., 2013) and food-waste monitoring (Jagtap & Rahimifard, 2019), and Bangladesh food-

safety research identifies gaps in control practices (Khan et al., 2022; Singha et al., 2025). The available sources do not establish the causal effect of WR on PE in the present sample. Plant managers can begin by establishing an avoidable-loss baseline by product family, assign a process owner and relate corrective actions to material yield and unit conversion cost. Environmental and financial benefits should be measured rather than assumed.

6.3 Supply chain integration and the proposed variability pathway

SCI may reduce variability across organizational boundaries through shared supplier specifications, reliable delivery commitments, cross-functional planning and customer-demand information. Its value depends on information accuracy and coordinated decisions, not simply on the volume of communication. Bangladesh agro-food research links supplier partnerships, customer relationships and information quality with performance, but does not demonstrate the PE pathway proposed here (Siju et al., 2024). Inconsistent produce maturity or late inbound shipments can reduce effective yield in an otherwise well-managed plant, whereas demand errors can result in finished-goods waste. Prior agro-food and wider supply-chain studies are consistent with the importance of upstream and downstream integration (Flynn et al., 2010; Kumar et al., 2020; Zhao et al., 2021; Shareef et al., 2025). These studies provide context; they do not estimate P3 or P6.

6.4 Production efficiency as the proposed link to business results

A model that links operational practices directly to profits may obscure the conversion mechanism. PE is proposed as a more proximal outcome, capturing yield, throughput, quality and input efficiency. Better PE can reduce unit costs, accelerate delivery and enhance customer performance, yet finance, prices and demand can still dictate the achieved margins. The mediation proposed in P5 is a testable explanation, not a finding from the secondary analysis. This distinction can help managers determine whether a technology investment failed to improve operations or whether an operational gain was not translated into commercial value. Both stages require measured indicators before a performance claim can be made.

6.5 Interpreting the historical evidence cautiously

The BAPA sample indicates low adoption of formal quality and lean practices, and subsequent Bangladesh research reports on positive correlations between technology-related constructs and operational results (Emon & Ahmed, 2025; Rashed et al., 2025). Taken together, these observations are consistent with, but do not prove, a capability-complementarity explanation. Differences in sample dates, definitions and units do not permit a combined effect estimate. BIDS-SEIP size-class concentration implies an additional boundary condition: in that sample, large firms account for most employment, but smaller firms might have different finance and implementation constraints. Future research should assess size-related differences directly rather than infer them from descriptive aggregates alone (BIDS, 2021).

7. Applications of the Integrated Framework

7.1 Theoretical application and distinct contribution

Three established theories are combined in a single staged explanation in Table 1 and Figure 1: digital capability improves information availability and process control, loss-prevention routines transform those insights into resource efficiency, and relational capability reduces external variability. Rather than treating each capability only as a parallel predictor of profitability, the framework positions PE as the proximal conversion mechanism through which TA, WR and SCI may contribute to BP. This is a theory-based organizing contribution, not a newly established empirical effect. P1–P6 can be tested against firm-level performance data using the measures in Appendix A (Barney, 1991; Hart, 1995; Dyer & Singh, 1998; Rashed et al., 2025; Emon & Ahmed, 2025). P7 can be tested by stratifying the same sample by enterprise size. Table A1 lists the core measurement domains for that fieldwork.Appendix B offers what prior conceptual work in this sector has not. It combines matched multi-informant survey measures with hard KPIs. It adds stochastic-frontier inefficiency estimation (Eqs. 10-11a). It includes formal tests of

complementarity (Eq. 9). Together these specify the data structure needed to falsify the model. That ex ante specification is the blueprint's main novel feature. Table B1 lists the validation safeguards for that agenda.

7.2 Managerial application and decisions supported by the evidence

Table 3 identifies historical gaps in quality, lean and financing practices. Table 4 and Figure 3 show why adoption programs should distinguish between the number of plants reached and the number of workers reached. Table 1 can help managers assign responsibilities: operations teams should monitor yield and defects (WR), engineering and IT should monitor process variability (TA), procurement and sales should monitor input and demand reliability (SCI). Each workstream can be linked to relevant KPIs as shown in Appendix A. Firms should use before-and-after baseline measurements and investment-specific cost analyses rather than assume that the descriptive rates predict future returns (BAPA, n.d.; BIDS, 2021; Singha et al., 2025; Siju et al., 2024).

7.3 Boundaries of application

The model can inform diagnosis and future data collection, but the present analysis does not establish the most appropriate mix of investment, confirm interactions or forecast financial returns of an enterprise. Appendix B provides candidate specifications for future firm-level tests; none is estimated in this article.

8. Managerial Implementation and Policy Implications

8.1 Staged plant-level improvement pathway

A staged improvement program begins with consistent definitions of saleable yield, defects, changeover loss and downtime. Teams can then digitize the most important information gaps, agree on supplier specifications and demand-sharing routines, and invest in advanced automation only when a business case has been documented. Formal adoption of TQM, JIT, HACCP and lean practices was limited in the historical BAPA sample (Table 3; Figure 2), so managers should assess underlying process discipline before selecting technology projects. This sequence is a managerial recommendation, not an intervention tested in this study (BAPA, n.d.; Dora et al., 2013; Rashed et al., 2025).

8.2 Production-efficiency dashboard

Managers should link a small set of objective plant measures to commercial outcomes: material yield, loss rate, first-pass quality, OEE where cycle standards are available, unit conversion cost, energy per saleable ton and on-time delivery (Appendix A, Table A2). Every KPI must have a baseline period, product-family definition, owner and target. Investment decisions should report both physical improvements and corresponding changes in cost or contribution margin; the current aggregate sources do not provide such firm-level values (BIDS, 2021; Singha et al., 2025). Managers should distinguish internal process losses from externally caused variability. As an example, frequent changeover losses are typically addressed by production teams, whereas rejected raw-material deliveries require a coordinated response from suppliers and quality teams. The necessary control mechanism is mapped in Table 1; possible process-assurance gaps are identified in Table 3; and supply-chain evidence highlights supplier relationships and information quality as priorities (Siju et al., 2024; Zhao et al., 2021).

8.3 Policy, finance and ecosystem design

Modernization financing should require a documented conversion-efficiency case rather than a mere equipment invoice. Only 16% of establishments in the BAPA sample reported formal institutional finance (Table 3), and recent research on technology adoption in Bangladesh also identifies capital constraints (Rashed et al., 2025). Investment proposals should specify the baseline material yield, quality loss, unit cost and target improvements, and the results should be measured after the investment. At the ecosystem level, small processors may benefit from shared testing, cold-chain services, maintenance services, workforce training and standardized supplier-

quality practices (BAPA, n.d.; Singha et al., 2025). Policy design should distinguish between two groups. Table 4 indicates that large firms account for the largest share of employment, and micro and small firms account for a substantial share of establishments; outreach should thus report both firm- and worker-level coverage. This dual-metric rule follows directly from the concentration evidence. Employment is 2.45 times more concentrated than establishment counts. Changing the denominator changes who looks like the main beneficiary. With firms as the unit, small plants dominate the picture. With workers as the unit, a few large plants dominate. Making that choice explicit is itself a policy contribution. P7 implies that size-targeted support may raise conversion returns. Support should combine process and food-safety training, practical information systems and coordinated post-harvest logistics, and should be evaluated using quantified loss, cost and market results (BIDS, 2021; Choudhury et al., 2024).

9. Limitations and Future Research

The evidence has four main limitations. To begin with, the BAPA source is a historical baseline of 50 enterprises, not a 2026 national prevalence survey. Second, it does not provide the matched firm-level measures and covariance structure required to test TA, WR, SCI, PE and BP relationships. Third, BIDS-SEIP is more about skills and labor structure than about the technical efficiency of plants and some monetary figures require careful arithmetic interpretation. Fourth, the peer-reviewed articles employed as the external context differ in terms of place, design, construct and estimator. Their coefficients cannot be pooled, and none tests P1–P6 using the two Bangladesh secondary sources. Future empirical research should use a stratified sample of Bangladeshi agro-processors and match multi-informant survey data with production records from the same firms and periods. Temporal order and changes could be assessed using a multi-wave or intervention design. The proposed relationships should be tested by subsector-specific analyses to determine whether perishability, batch structure and asset intensity changes the proposed relationships. Appendix B describes candidate procedures, which are subject to sample size and identification.

10. Conclusion

This conceptual framework treats performance in Bangladesh's agro-processing industry as a resource-conversion problem involving plant capabilities, supplier coordination and business outcomes. The descriptive BAPA baseline indicates that historically there has been a low level of adoption of formal quality, lean and financing practices; reported output to operating hours is 1.473 metric tons per hour but does not represent a firm-level efficiency estimate. In the BIDS-SEIP sample, large firms account for 81.5% of employment even though they make up 38.5% of establishments. These calculations are specific to their respective sources and do not establish causal relationships among the five constructs. The suggested contribution is a testable sequence: adoption of technology enhances process visibility, waste-reduction capability converts information into lower losses, and supply chain integration minimizes cross-boundary variability. P7 adds a size-moderation claim drawn from the paper's own data. It ties the descriptive evidence to the testable agenda. The paper also contributes a reproducible secondary-analysis template. It documents inconsistencies instead of hiding them. Three further contributions follow from the framework and appendices. First, a construct boundary that separates TA from lean practices. Second, novel concentration diagnostics with direct policy value. Third, a matched-measure blueprint for future firm-level tests. The framework proposes that these capabilities are linked to business performance through production efficiency; the propositions of complementarity and mediation are yet to be tested. Managers can apply the framework to put measurement, stabilization and coordinated investment at the forefront, and researchers can apply the KPIs in Appendix A and optional models in Appendix B to matched primary data. The paper does not estimate a national efficiency level nor does it show that the adoption of the three capabilities will have a causal effect on profitability.

Appendix A. Recommended Firm-Level Measurement and Objective KPI Set

Table A1: Core measurement domains for confirmatory fieldwork

Construct	Codes	Domains	Preferred evidence
Technology adoption	TA1-TA5	Digital monitoring; automation/control; integrated planning; batch traceability; predictive/condition-based maintenance	7-point implementation scale + system logs
Waste reduction	WR1-WR6	Loss measurement; standard work; root-cause improvement; preventive maintenance; reuse/by-product recovery; energy/material intensity improvement	7-point scale + loss/yield records
Supply chain integration	SCI1-SCI6	Cross-functional planning; supplier specifications; forecast sharing; quality feedback; shared inventory/delivery information; customer integration	7-point scale + supplier/customer records
Production efficiency	PE1-PE5	Unit conversion cost; throughput; yield; downtime/OEE; defect/rework	7-point relative performance + objective KPIs
Business performance	BP1-BP5	Profitability; sales growth; market share/competitiveness; export readiness; customer performance	Finance/management respondent; relative-to-competitor scale

Source: *adapted from the cited operations, supply-chain and technology-adoption literature; wording should be pilot-tested in Bangladesh.*

Table A2: Objective production-efficiency KPIs

KPI	Formula	Unit	Measurement note
Material yield	Conforming saleable output / raw-material input x 100	%	Use consistent mass basis; separate unavoidable conversion/moisture change.
Process loss rate	Avoidable abnormal process loss / raw-material input x 100	%	Define normal vs avoidable loss by product family.
Throughput	Conforming output / operating time	MT/hour	Use bottleneck or line-level time where possible.
OEE	Availability x performance x quality	%	Use only where design cycle/capacity is measurable.
Energy intensity	Energy consumed / conforming output	kWh/MT or MJ/MT	Normalize by product family or thermal duty.
Labor productivity	Conforming output / direct labor hours	MT/labor-hour	Control for automation and product mix.
Defect/rework rate	Reworked or rejected output / total output x 100	%	Separate rework from final scrap/rejection.
Unit conversion cost	Processing cost excluding raw material / conforming output	BDT/MT	Use consistent cost accounting across periods.

Source: *authors' specification; objective records should be matched to the same period as survey measures.*

Appendix B. Optional Specifications for Future Firm-Level Tests (Not Estimated)

Prospective mediation and complementarity models

In future primary-data studies, the same firms and accounting periods should provide matched TA, WR, SCI, PE and BP measures. Equations (7)-(9a) specify candidate mediation and interaction models for prospective testing only; no coefficient is estimated in the present paper.

$$\begin{aligned} \mathrm{PE}_i = {} & \beta_0 + \beta_1 \mathrm{TA}_i + \beta_2 \mathrm{WR}_i + \beta_3 \mathrm{SCI}_i \\ & + \beta_4(\mathrm{TA}_i \times \mathrm{WR}_i) + \beta_5(\mathrm{TA}_i \times \mathrm{SCI}_i) \\ & + \beta_6(\mathrm{WR}_i \times \mathrm{SCI}_i) + \Gamma' X_i + \varepsilon_i \end{aligned} \tag{7}$$

The business-performance equation separates the proposed PE mediator from any residual direct effects of the three capability variables.

$$\mathrm{BP}_i = \alpha_0 + \delta \mathrm{PE}_i + \theta_1 \mathrm{TA}_i + \theta_2 \mathrm{WR}_i + \theta_3 \mathrm{SCI}_i + \Lambda' X_i + u_i \quad (8)$$

Potential indirect effects should be evaluated using bootstrap confidence intervals. Complementarity would require statistically tested interaction terms, appropriate scaling and economic interpretation; merely observing positive separate coefficients would not demonstrate it.

$$\mathrm{TotEff}_{\mathrm{TA}} = \theta_1 + \beta_1 \delta, \qquad \mathrm{TotEff}_{\mathrm{WR}} = \theta_2 + \beta_2 \delta \qquad \mathrm{TotEff}_{\mathrm{SCI}} = \theta_3 + \beta_3 \delta \quad (9)$$

$$\frac{\partial \mathrm{PE}_i}{\partial \mathrm{TA}_i} = \beta_1 + \beta_4 \mathrm{WR}_i + \beta_5 \mathrm{SCI}_i \quad (9a)$$

Candidate objective efficiency models

Prospective studies could compare survey-based PE with independently recorded inputs and conforming outputs. Equations (10)-(11a) outline candidate stochastic-frontier and inefficiency models, subject to valid product normalization and sufficient sample size (Aigner et al., 1977; Battese & Coelli, 1995).

$$\ln Y_i = \alpha_0 + \alpha_K \ln K_i + \alpha_L \ln L_i + \alpha_M \ln M_i + v_i - u_i \quad (10)$$

$$u_i = \gamma_0 - \gamma_1 \mathrm{TA}_i - \gamma_2 \mathrm{WR}_i - \gamma_3 \mathrm{SCI}_i + \Psi' Z_i + \eta_i \quad (10a)$$

$$\mathrm{TE}_i = \exp(-u_i), \qquad 0 < \mathrm{TE}_i \leq 1 \quad (11)$$

$$\ln Y_i = \alpha_0 + \sum_j \alpha_j \ln x_{ji} + \frac{1}{2} \sum_j \sum_\ell \alpha_{j\ell} \ln x_{ji} \ln x_{\ell i} + v_i - u_i \quad (11a)$$

Here, Y denotes conforming saleable output or value added; K is productive capital, L is labor input, M is material and energy input, v is symmetric error and u is one-sided inefficiency. Negative estimated capability coefficients in a correctly specified inefficiency-effects model would imply lower inefficiency. Multiproduct data require consistent product-family or value-added measures. These models remain proposals, not reported results.

$$H_E = -\frac{\sum_{k=1}^{K} e_k \ln(e_k)}{\ln K} = 0.4379, \qquad K = 4 \quad (3a)$$

$$\mathrm{LQ}_k = \frac{e_k}{f_k} \quad (3b)$$

$$G = 1 - \sum_{j=1}^{J} (Y_j + Y_{j-1})(X_j - X_{j-1}) \quad (3c)$$

Measurement and validation safeguards

Future surveys should use multiple respondents and comparable objective records for yield, throughput, losses, quality and unit cost. Reflective constructs should be assessed for reliability and discriminant validity, whereas formative measures should be assessed for collinearity and the significance of their weights (Hair et al., 2020; Henseler et al., 2015). Reverse causality is possible because better-performing firms may have greater capacity to finance technology and integration. Future studies should establish measurement timing and, where appropriate, use panel fixed effects, lagged outcomes or other design-based controls. Predictive performance should be evaluated on held-out data rather than in-sample fit alone (Shmueli et al., 2019).

Table B1: Suggested validation safeguards for future primary-data studies

Component	Required procedure	Minimum reporting
Sampling	Stratify by subsector and firm size; power analysis based on smallest effect of interest; target >300 usable firms where feasible.	Report frame, invitations, response rate and nonresponse diagnostics.
Measurement	Multi-informant, two-wave where feasible; validated scales; objective PE KPIs.	CR/rho_A, AVE, HTMT; VIF and weights for composites.
Structural model	Direct, mediated and interaction effects with bootstrap CIs.	β, SE, t, p, 95% CI, R^2, f^2 and marginal-effect plots.
Efficiency model	SFA or DEA sensitivity model using output, labor, capital, material/energy.	TE distribution; alternative functional form and outlier robustness.
Endogeneity	Lagged BP, defensible instruments/panel effects or copula diagnostics.	Show whether main path signs/magnitudes survive correction.
Prediction	Holdout prediction / PLSpredict plus benchmark model.	Out-of-sample RMSE/MAE and predictive relevance.
Heterogeneity	Firm size, subsector, export orientation, location.	MGA or interaction tests with measurement-invariance checks.

Source: *authors' methodological specification based on Hair et al. (2020), Henseler et al. (2015), Aigner et al. (1977) and standard production-efficiency practice.*

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