

Integrated Semi-Automation Improves Throughput, Product Consistency, and Hygiene in Small-Scale Milk-Ice Production

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ABSTRACT

Usaha pangan skala kecil sering menghadapi keterbatasan simultan pada kapasitas produksi, konsistensi produk, higiene, dan pengendalian proses. Penelitian ini mengevaluasi MILKONIX (Smart Integrated Milk Ice Stick Line), sistem semiotomatis berskala tepat yang diterapkan pada UMKM Milkyfun di Malang, Indonesia. Desain lapangan sebelum-sesudah pada satu lokasi digunakan untuk menilai kinerja operasional selama 10 batch produksi, mutu 100 produk pada setiap kondisi, dan uji fungsional terpilih. MILKONIX mengintegrasikan pasteurisasi, pencampuran terkendali, pengisian presisi, conveyor, pemasangan stik, pembekuan terkendali, clean-in-place parsial, sensor, pencatatan batch digital, pelatihan operator, dan SOP. Waktu produksi aktif turun 43,3%, kapasitas per batch naik 50,0%, kapasitas harian naik 125,0%, dan produktivitas tenaga kerja naik 200,0%. Keseragaman volume meningkat dari 78% menjadi 97%, cacat produk turun dari 9% menjadi 2%, waktu pembersihan turun 51,1%, dan kepatuhan sanitasi meningkat dari 62% menjadi 91%. MILKONIX menunjukkan potensi otomasi sosioteknis terintegrasi untuk meningkatkan kinerja produksi pangan skala kecil.

Small food enterprises often face simultaneous constraints in throughput, product consistency, hygiene, and process control. This study evaluated MILKONIX (Smart Integrated Milk Ice Stick Line), a right-sized semi-automated system implemented at Milkyfun, Malang, Indonesia. A single-site before-and-after field design assessed operational performance across 10 production batches, product quality in 100 units per condition, and selected functional tests. MILKONIX integrated pasteurization, controlled mixing, precision filling, conveyor transfer, stick insertion, controlled freezing, partial clean-in-place sanitation, sensors, digital batch logging, operator training, and standardized procedures. Active production time decreased by 43.3%, batch capacity increased by 50.0%, daily capacity by 125.0%, and labor productivity by 200.0%. Volume uniformity increased from 78% to 97%, defects fell from 9% to 2%, cleaning time decreased by 51.1%, and sanitation compliance rose from 62% to 91%. MILKONIX demonstrates how integrated socio-technical automation can improve small-scale food production performance.



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INTRODUCTION

Small food and dairy enterprises occupy an important position between household processing and industrial manufacturing. They can respond quickly to local demand, create employment, and transform perishable raw materials into higher-value products, yet their production systems are commonly constrained by limited capital, compact facilities, manual routines, and informal process control. These constraints are especially consequential for frozen dairy products because the same operations that determine output - mixing, filling, freezing, cleaning, and handling - also shape product uniformity and hygienic risk. Recent food-processing literature increasingly treats this challenge as one of digital and operational transformation rather than simple equipment substitution. Reviews of food-processing

MSMEs describe digital technologies as potential enablers of operational efficiency and sustainability, but also emphasize the need for financial investment and skill development for effective adoption (Ranjini et al., 2025). Evidence from food-sector SMEs likewise indicates that frugal digital technologies can improve innovation performance by streamlining production and information flows, although benefits depend on the organizational context in which they are deployed (Mashoko, 2025). For small producers, therefore, increasing output is valuable only if variability, defects, sanitation, and resource use can be controlled at the same time.

Automation has long been used in dairy and food processing to stabilize operating parameters, reduce repetitive manual work, and support process monitoring. Reviews of dairy automation describe growing use of programmable control, sensing, and integrated supervision to improve repeatability and reduce operator dependence (Heema et al., 2022), while process-monitoring literature highlights the role of sensors in translating temperature, flow, level, and related variables into control actions that maintain operating conditions near their set points (Adelolu, 2004). Earlier work on distributed control systems similarly anticipated that modular control architectures, once associated mainly with large continuous plants, could be applied to smaller batch-processing users (Dahm & Mathur, 1990). More recent Industry 4.0 research in food manufacturing shows that legacy production systems can be augmented with IoT, analytics, and cyber-physical monitoring rather than replaced outright, allowing traditional manufacturers to improve consistency and operational visibility (Konur et al., 2023). In SMEs, however, automation is not simply a scaled-down version of a large industrial line. Adoption depends on process readiness, compatibility with workflows, worker capability, maintenance resources, and the economic logic of modest production volumes (Moreira et al., 2024; Santos et al., 2019). Collaborative-automation research in food production also stresses that feasibility must be evaluated in terms of throughput, ergonomics, technical constraints, and economic benefit rather than machine capability alone (Accorsi et al., 2019).

The problem is particularly evident in frozen milk products. Product texture and stability depend on the thermal history of the mix and the freezing stage, while filling accuracy affects portion consistency, package integrity, and downstream handling. Modeling of ice-cream freezing demonstrates that freezing performance is governed by coupled heat-transfer and phase-change behavior, so unstable thermal conditions can produce heterogeneous outcomes (Giudici et al., 2021). At the same time, milk-based products are susceptible to microbial contamination when raw materials, water, equipment surfaces, or handling practices are poorly controlled. Studies on raw milk and dairy products have reported *Bacillus cereus* and other bacterial hazards, reinforcing the importance of hygienic design, sanitation, and minimized post-process exposure (Ahmed et al., 1983; Hassan et al., 2010; Reta et al., 2016; Garbaj et al., 2016). Automation can contribute to this control problem when it reduces open handling and improves repeatability; broader reviews of robotics in food processing identify precision, productivity, hygiene, and reduced repetitive human intervention as recurring motivations for adoption (Raffik et al., 2023). Thus, for small frozen-dairy producers, productivity engineering and hygiene engineering cannot be separated.

A further gap concerns the unit of intervention. Many technology-transfer programs for small enterprises introduce a single machine to address an isolated bottleneck. Such approaches can generate useful local improvements: an Indonesian food-SME case integrating material handling and processing reduced cycle time by about 39% (Anggrahini et al., 2020), while recent small-scale food equipment studies report faster and more consistent operations after automating wrapping or filling tasks (Basar et al., 2025; Mouleeshuwarappabu et al., 2025). However, task-level improvement does not necessarily translate into system-level performance if upstream and downstream constraints remain. A faster mixer does not increase final throughput if filling remains manual; a precision filler does not assure consistent final quality if freezing is unstable; and a closed process does not sustain hygienic gains if cleaning, maintenance, and operator practices are not standardized. Simulation and implementation studies in food manufacturing similarly show that throughput gains from automation vary with production configuration and bottleneck structure rather than arising automatically from the presence of robotics (Baek et al., 2024). This creates a systems-level research question: can a compact semi-automated line designed around SME constraints simultaneously improve production efficiency, product consistency, hygienic practice, and operational control?

MILKONIX (Smart Integrated Milk Ice Stick Line) was developed to address this question at Milkyfun, a home-based micro and small enterprise producing milk ice sticks in Wringinanom, Poncokusumo, Malang, Indonesia. Before the intervention, production was dominated by manual weighing, mixing, filling, stick placement, transfer, freezing, and cleaning. One batch required approximately 180 min of active production time and produced about 400 sticks; daily capacity was about 800 sticks with four workers. Only 78% of products met the defined volume-uniformity criterion, the overall defect rate was 9%, cleaning required approximately 45 min per batch, sanitation compliance was 62%, and production records were largely informal. These conditions resemble the low-automation environments described in food-SME studies, where manual repetitive operations constrain both capacity and consistency and where high-capital robotic solutions may be difficult to justify (Accorsi et al., 2019; Baek et al., 2024). Accordingly, the intervention was designed as 'right-sized' semi-automation: sufficient automation to control critical operations while retaining human oversight and fitting the spatial, financial, and maintenance realities of a small enterprise.

The intervention combined a 35-L raw-material hopper, a 30-L pasteurization tank, a 30-L controlled mixer, a food-grade transfer system, a precision filler, a 2.5-m conveyor, an automated stick-insertion mechanism, a controlled freezing chamber, a partial clean-in-place (CIP) circuit, sensors, a centralized control panel, and a local digital dashboard. Importantly, the technological intervention was accompanied by operator training, standard operating procedures (SOPs), maintenance routines, sanitation documentation, and batch-based digital records. The monitoring component is consistent with the broader shift toward evidence-based process control in food manufacturing, in which online or near-real-time sensing supports corrective action and quality assurance (Adelolu, 2004; Griffin et al., 2001). Contemporary Quality 4.0 research further frames digital inspection and traceability as socio-technical capabilities that link sensing, analytics, conformity verification, and management standards rather than as isolated IT functions (Sánchez-Rodríguez et al., 2025). This architecture therefore reflects a socio-technical view of automation in which equipment performance depends on alignment among machine functions, process parameters, worker competence, and management routines, consistent with evidence that information technology and human-resource capabilities must be strategically coordinated in manufacturing SMEs (L'Écuyer et al., 2019).

The central hypothesis was that integrated semi-automation would generate simultaneous gains rather than a single-dimensional increase in speed. Specifically, the study expected (i) shorter active processing and cleaning times; (ii) greater batch and daily throughput; (iii) improved volume, weight, freezing, and assembly consistency; (iv) improved hygiene through reduced manual contact and standardized sanitation; and (v) greater operator capability and process traceability through training, SOPs, and digital monitoring. This expectation is aligned with emerging smart-manufacturing research in food systems, where integrated combinations of production engineering, IoT, analytics, and maintenance are proposed to reduce non-value-added time and improve production efficiency (Valles et al., 2025). Data-oriented food-processing studies likewise emphasize that dashboards and analytics can support resource optimization when they are connected to operational decision making (Hassani et al., 2025). The novelty of MILKONIX therefore lies less in any one machine component than in evaluating a compact production architecture in which automation, hygienic design, data capture, and workforce capability are treated as one intervention.

Accordingly, this study evaluated the operational and product-level effects of MILKONIX using a before-and-after field design. The primary outcomes were active production time, production capacity, volume uniformity, defect rate, and sanitation compliance. Secondary outcomes included freezing time, cleaning time, energy use, labor productivity, operator competency, acceptance, and selected business-performance indicators. The study also examined the functional reliability of the integrated line and interpreted the findings against the broader literature on scalable automation for small food enterprises. Because the available source data contained aggregated baseline and post-intervention measurements rather than complete batch-level raw datasets for every endpoint, the statistical analysis was intentionally conservative: descriptive effect measures were emphasized, and inferential comparisons were restricted to outcomes with explicit product-level denominators. This design does not support population-level causal claims, but it can provide field evidence on whether a coordinated, appropriately scaled automation package produces internally consistent improvements across technical, quality, hygiene, and human-capability domains.

METHOD

Study design and setting

This applied engineering study used a single-site quasi-experimental before-and-after design. The study was conducted at UMKM Milkyfun in Wringinanom, Poncokusumo District, Malang Regency, East Java, Indonesia. Milkyfun produces milk ice sticks in small plastic packages using milk, sugar, water, flavoring ingredients, and related formulation components. The pre-intervention production system relied on separate household-scale equipment and manual handling. The intervention was evaluated under routine production conditions so that measured performance reflected the operational constraints of the enterprise rather than laboratory-only performance.

Baseline assessment included direct observation, workflow mapping, time measurement, interviews with the owner and operators, review of production practices, and a hygiene checklist. The initial process comprised ingredient preparation, manual mixing, manual filling, manual stick placement, product transfer, household-freezer freezing, equipment washing, packaging, and storage. The baseline measurements established the reference condition for time, capacity, labor involvement, product uniformity, defects, energy consumption, sanitation compliance, and operator knowledge. The reported baseline values were 180 min active production time per batch, 400 sticks per batch, two batches per day, four direct workers, 45 min cleaning time, 12.8 kWh energy consumption per batch, 78% volume uniformity, 9% total defects, 62% sanitation compliance, and a mean operator knowledge/skill score of 56/100.

MILKONIX intervention

MILKONIX was designed as a semi-automated, sequential line that integrated previously fragmented operations. Raw ingredients were introduced through a 35-L hopper and transferred to a 30-L heating/pasteurization vessel fitted with a temperature sensor, heating element, light agitation, and time control. The vessel reached 72°C in approximately 18 min at the working capacity and maintained the product within 72–74°C. Material was then transferred through a closed line to a 30-L mixing tank. Mixing speed could be set between 60 and 120 rpm, with 90 rpm for 12 min selected as the operational setting that produced the most homogeneous mixture during functional testing.

After mixing, the formulation was delivered by a food-grade pump to a precision filling module synchronized with a 2.5-m conveyor. The nominal fill volume was 60 mL per package, with an acceptable operational range of 58–62 mL. The conveyor could operate between 2 and 5 m min⁻¹ and was typically set at 3.5 m min⁻¹ to align package transfer with filling and stick insertion. A mechanical actuator inserted the sticks after filling. Filled units were subsequently transferred to an integrated freezing chamber with a nominal capacity of 600 sticks and an operating target between -17°C and -20°C. During functional testing, mean chamber temperature was -18.3°C with reported fluctuation of ±1.2°C.

The line also incorporated a partial CIP system for the mixing tank, pump, product lines, and filling nozzles. A sanitation cycle comprised initial rinsing, circulation of cleaning solution, final rinsing, and drying, with a total cycle time of approximately 22 min. A centralized panel provided control of pasteurization temperature, mixing speed and duration, filling settings, conveyor speed, freezing temperature, alarms, and emergency stop functions. Process parameters were transferred to a local digital dashboard accessible from a computer or smartphone. The dashboard recorded key parameters at 5-s intervals and grouped the records by production batch.

Implementation and operator preparation

Implementation followed a staged process of needs assessment, participatory design, prototype assembly, installation, functional testing, operator training, SOP development, and routine-use evaluation. Three principal operators participated in three training sessions that combined explanation, demonstration, hands-on practice, simulated faults, sanitation procedures, digital monitoring, and basic maintenance. The program produced 10 operating SOPs and one quality-assurance manual covering ingredient preparation, pasteurization, mixing, filling and stick insertion, freezing, sanitation/CIP, maintenance, packaging, storage, and occupational safety. This organizational component was treated as part of the intervention because the study sought to evaluate an integrated production system rather than a machine in isolation.

Functional and production-performance measurements

Functional tests were undertaken after mechanical, electrical, piping, sensor, and control installation. Temperature-sensor readings were compared with a calibrated digital reference thermometer in 10 measurements. Filling accuracy was evaluated in 200 packages at a 60-mL target. Stick insertion was evaluated in 200 filled packages. Control-panel functions were tested in 20 repetitions, and digital-record completeness was evaluated over 10 batches. Production performance after implementation was measured over 10 production batches. The principal operational indicators were mixing time, filling time, stick-insertion time, active production time, freezing time, complete cycle time, batch capacity, batches per day, daily capacity, number of direct workers, labor productivity, cleaning time, energy consumption per batch, and calculated energy use per stick.

Active production time was defined in the project dataset as the operator-active duration from preparation until products were ready to enter the freezing stage. Freezing duration was analyzed separately because it proceeded after active product handling. Total cycle time was therefore calculated as active production time plus freezing time. Labor productivity was calculated as daily output divided by the number of direct workers. Energy intensity was calculated from measured energy per batch divided by products per batch. These derived metrics permitted comparison of output efficiency despite the change in batch size between the two conditions.

Product-quality and hygiene assessment

Product quality was assessed using samples drawn from 10 production batches, with 100 products evaluated for each study condition. The recorded indicators included volume uniformity, weight uniformity, color and taste homogeneity, texture, ice-crystal uniformity, package leakage, freezing failure, stick-position accuracy, package integrity, total defects, storage stability, and consumer acceptance. Volume was checked against the operational range of 58–62 mL, and product mass was measured using a digital balance with 0.1-g resolution. Sensory-homogeneity attributes were scored on a five-point scale according to the project protocol. Thirty consumers participated in the acceptance assessment.

Hygiene evaluation included a sanitation-compliance checklist, cleaning time, frequency of manual product contact, use of personal protective equipment, completion of sanitation procedures, and digital sanitation records. The project report also contains microbiological and ATP-cleanliness values; however, that section explicitly states that highlighted figures are recommended/provisional data requiring alignment with actual laboratory measurements and field observations before they are used as factual results. To preserve evidentiary integrity, those microbiological values were not used as confirmatory outcomes in the present manuscript. The hygiene claims in this article are therefore limited to documented process indicators such as manual-contact reduction, cleaning time, sanitation compliance, PPE use, and completion of sanitation records.

Operator competency and user acceptance

Operator competency was assessed before and after training using a 100-point test covering machine functions, operating sequence, sanitation, safety, and process monitoring. Individual pretest scores were 58, 54, and 56; corresponding post-test scores were 88, 84, and 86. Practical competencies were additionally rated for machine operation, production sequencing, sanitation/CIP, digital-panel reading, routine maintenance, minor-fault handling, digital-log completion, and PPE compliance. Partner acceptance was assessed after 10 production batches using a five-point Likert questionnaire completed by the owner and three operators. The questionnaire addressed ease of operation, usefulness, safety, cleaning, fit with enterprise needs, production efficiency, product quality, maintenance, intention to continue use, and overall satisfaction.

Statistical analysis

The analysis prioritized effect magnitude and transparency. For continuous or count indicators reported only as condition-level aggregates, absolute change and relative percentage change were calculated as $(\text{post} - \text{pre})/\text{pre} \times 100\%$. For time and defect outcomes, negative values indicate desirable reductions; in the Results, reductions are generally expressed as positive percentages for readability. Percentage-point changes were also reported for proportions. Active throughput was calculated as sticks per hour of active production, and full-cycle throughput as sticks per hour including freezing. Energy intensity was calculated directly from the unrounded batch-level energy and capacity values; this yielded 0.0320 kWh stick⁻¹ before and 0.0182 kWh stick⁻¹ after implementation, a 43.2% reduction. This differs

slightly from the 43.8% value in the source table because that table used the rounded post-intervention intensity of 0.018 kWh stick⁻¹.

For product-level binary outcomes with explicit denominators of 100 products per condition, exploratory two-sided Fisher exact tests were calculated from the reported counts. Wilson 95% confidence intervals were used to describe selected binomial proportions. Because products were sampled from 10 batches but batch-specific outcome distributions were not available, product-level tests can underestimate clustering and were treated as exploratory rather than confirmatory. No p-values were generated for endpoints lacking raw replicate data. Likewise, an inferential paired test was not applied to the three operator competency scores because all operators improved by exactly 30 points, producing zero variance in the paired differences. Analyses were therefore interpreted as field-performance evidence from one implementation site, not as population-level causal estimates.

Table 1. MILKONIX architecture and operational settings used during field evaluation.

Module	Key specification / setting	Primary function
Raw-material hopper	35 L; residual material in line <1%	Receives and transfers ingredients
Pasteurization vessel	30 L; 72–74 °C; ~18 min to reach 72 °C	Controlled thermal treatment
Mixing tank	30 L; 90 rpm for 12 min selected	Homogenizes formulation
Filling system	60 mL target; acceptable range 58–62 mL	Standardizes portion volume
Conveyor	2.5 m; selected speed 3.5 ± 0.1 m min ⁻¹	Synchronizes package transfer
Stick insertion	Mechanical actuator; 96% correct in 200 trials	Positions sticks after filling
Freezing chamber	600-stick capacity; mean –18.3 °C	Controlled product freezing
Partial CIP	22-min cycle for tank, pump, lines, and nozzles	Standardizes cleaning
Control and dashboard	Sensors, alarms, emergency stop; 5-s data logging	Process control and batch traceability

Note. Specifications and settings are those reported in the supplied field dataset; settings were selected during functional testing.



Figure 1. MILKONIX process architecture. Product flow is integrated with partial CIP and a digital control layer that records process parameters by batch.

RESULTS AND DISCUSSION

Functional performance of the integrated line

All major MILKONIX modules operated within the predefined functional ranges during commissioning. The pasteurization vessel reached 72°C in approximately 18 min and maintained the product between 72 and 74°C. Mean sensor deviation from the reference thermometer was $\pm 0.5^\circ\text{C}$, within the $\pm 1^\circ\text{C}$ tolerance specified in the project protocol. Mixing at 90 rpm for 12 min produced the best observed combination of color, viscosity, taste distribution, and absence of visible settling; motor-speed deviation at this setting was approximately ± 2 rpm. The filling unit delivered a mean of 60.2 ± 1.4 mL. Of 200 filling trials, 194 (97.0%; Wilson 95% CI 93.6–98.6%) fell within the 58–62 mL range. Six out-of-range fills were associated with air in the line at start-up and improved after venting and pump-pressure adjustment.

The conveyor operated without reported slippage or jamming across the tested speed range, with 3.5 ± 0.1 m min⁻¹ selected as the best synchronization point. Stick insertion was correct in 192 of 200 packages (96.0%; 95% CI 92.3–98.0%); the remaining eight required correction because the package opening shifted relative to the insertion point. The freezing chamber maintained an average temperature of -18.3°C with $\pm 1.2^\circ\text{C}$ fluctuation and a maximum measured front-to-back temperature difference of 1.5°C . The partial CIP cycle was completed in approximately 22 min. All tested control-panel and safety functions operated successfully in 20 of 20 repetitions, and the dashboard stored complete records for all 10 monitored batches. These results established that the integrated system was sufficiently stable for routine before-and-after performance evaluation.

Production time, capacity, and resource efficiency

The clearest effect of MILKONIX was the simultaneous reduction in process time and increase in output. Mixing time decreased from 30 to 12 min (-60.0%). Filling time declined from 70 min for a 400-stick batch to 32 min for a 600-stick batch (-54.3% in elapsed time despite 50% more units). Stick-insertion time decreased from 45 to 24 min (-46.7%). These changes reduced active production time from 180 to 102 min per batch, a 43.3% reduction. Freezing time fell from 150 to 112 min (-25.3%), and total cycle time declined from 330 to 214 min (-35.2%). Figure 2 summarizes these time reductions.

The reduction in time was accompanied by an increase in batch capacity from 400 to 600 sticks (+50.0%). The number of completed batches per day rose from two to three, producing an increase in daily capacity from 800 to 1,800 sticks (+125.0%). On an active-time basis, throughput increased from 133.3 to 352.9 sticks h⁻¹, corresponding to a 164.7% increase. When freezing time was included, full-cycle throughput increased from 72.7 to 168.2 sticks h⁻¹ (+131.3%). These derived measures show that the gain was not merely a consequence of a larger batch: substantially more product was generated per unit of process time.

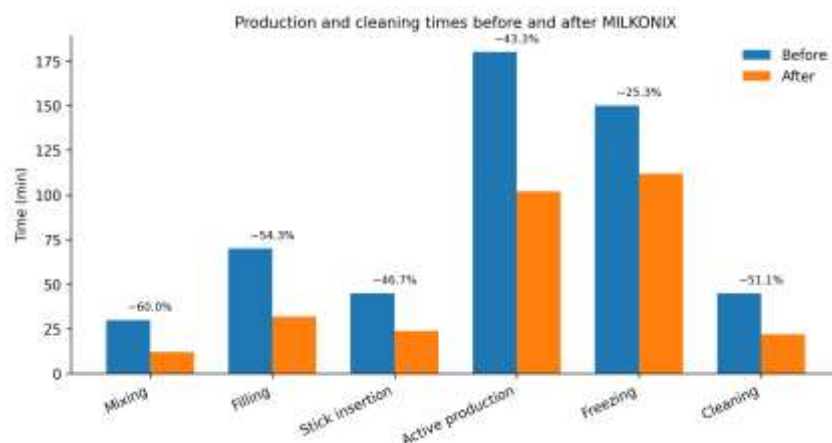


Figure 2. Production and cleaning times before and after MILKONIX. Percent labels show reductions relative to the manual baseline.

Direct labor involvement decreased from four to three workers while output increased. Daily labor productivity therefore rose from 200 to 600 sticks worker⁻¹ day⁻¹, a 200% increase. The practical significance of this change was a reallocation of labor rather than complete labor substitution. The project records indicate that time previously spent on repetitive filling and handling could be redirected

to ingredient preparation, packaging, quality checking, and production recording. Cleaning time decreased from 45 to 22 min per batch (-51.1%), consistent with the introduction of the partial CIP sequence.

Energy consumption per batch decreased from 12.8 to 10.9 kWh (-14.8%) even though batch output increased by 50%. More importantly, energy intensity calculated from the unrounded batch values declined from 0.0320 to 0.0182 kWh per stick (-43.2%). Thus, the energy result is stronger when normalized to output. The program target of a 15% reduction in batch energy was narrowly missed by 0.2 percentage points, but the per-unit energy reduction indicates a substantial improvement in resource productivity. Figure 3 presents the relative changes in major operational outcomes.

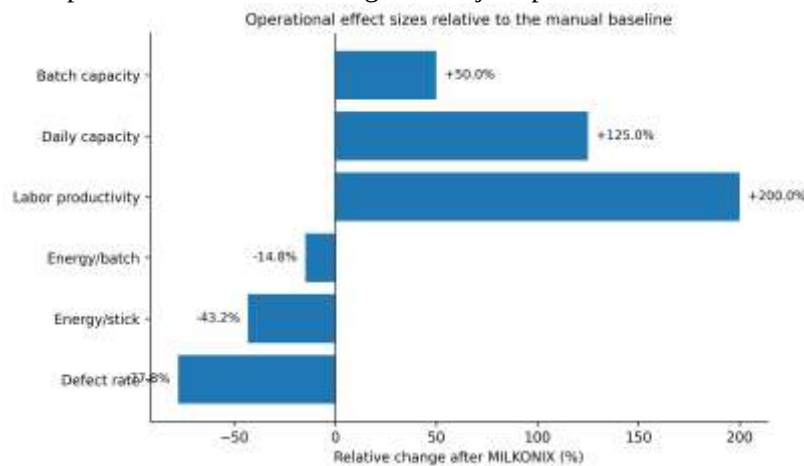


Figure 3. Relative operational changes after MILKONIX. Positive values indicate increased capacity or productivity; negative values indicate reductions in energy use or defects.

Product consistency and defect reduction

Product-level quality indicators improved across multiple dimensions. Volume uniformity increased from 78% to 97%, an absolute increase of 19 percentage points and a relative increase of 24.4%. With 100 products assessed in each condition, the post-intervention proportion had a Wilson 95% CI of 91.5–99.0%, compared with 68.9–85.0% at baseline. An exploratory Fisher exact comparison yielded $p < 0.001$. Weight uniformity similarly increased from 80% to 96% (+16 percentage points; exploratory Fisher $p < 0.001$). These results are consistent with the functional filling test and support the interpretation that automated dosing reduced operator-dependent variation.

The effects extended beyond portion size. Color-homogeneity scores increased from 3.2 to 4.6 on the five-point scale, taste homogeneity from 3.1 to 4.5, and texture homogeneity from 3.0 to 4.4. Because raw panel-level scores were not available, these changes were not subjected to inferential testing. Ice-crystal uniformity increased from 72% to 95% (+23 percentage points), with an exploratory Fisher test indicating a clear difference between the pooled product counts ($p < 0.001$). The result is consistent with the reduction in freezing time and the more uniform thermal environment recorded in the controlled chamber.

Stick-position accuracy increased from 82% to 96% (+14 percentage points; exploratory Fisher $p = 0.003$). Package integrity increased from 91% to 98% (+7 percentage points), although this difference was not statistically decisive in the exploratory product-level analysis (Fisher $p = 0.058$). Leakage declined from 3.0% to 0.7%, and incomplete or uneven freezing from 3.5% to 0.8%, according to the project dataset. Overall defects decreased from 9% to 2%, a 7-percentage-point absolute reduction and a 77.8% relative reduction. In the pooled 100-product comparison, this defect difference was borderline under Fisher's exact test ($p = 0.058$), illustrating why the magnitude of change should not be confused with certainty from a modest product sample.

Storage stability increased from 84% to 96% during the 14-day observation period at -18°C . Mean consumer-acceptance score increased from 3.4 to 4.5 out of 5, and 27 of 30 consumers (90%; Wilson 95% CI 74.4–96.5%) reported liking or strongly liking the post-intervention product, compared with 70% reported for the baseline product. The source data do not provide paired individual consumer responses, so no paired inferential test was performed. Figure 4 shows the direction and magnitude of changes in selected quality and process-hygiene indicators.

Hygiene-process performance and traceability

MILKONIX reduced the number of reported manual contacts with ingredients or product from an average of 28 to 6 contacts per batch, a 78.6% reduction. The change reflects closed transfer between the pasteurization, mixing, and filling stages and reduced need for manual pouring. Sanitation compliance increased from 62% to 91%, a 29-percentage-point improvement, and PPE compliance increased from 58% to 93%. Compliance with the documented cleaning sequence rose from 60% to 95%. Completion of sanitation logs increased from 15% to 100% because the operating sequence and sanitation status were recorded digitally.

These hygiene improvements should be interpreted as process-control outcomes rather than direct proof of microbiological safety. The project source includes provisional microbiological values, but it also explicitly requires those values to be aligned with verified laboratory measurements before being used as factual results. Accordingly, no microbial-reduction claim is made here. Nevertheless, the combination of fewer manual contacts, shorter and standardized cleaning, higher sanitation compliance, and complete batch-level sanitation records indicates that the process became more controllable and auditable after the intervention.

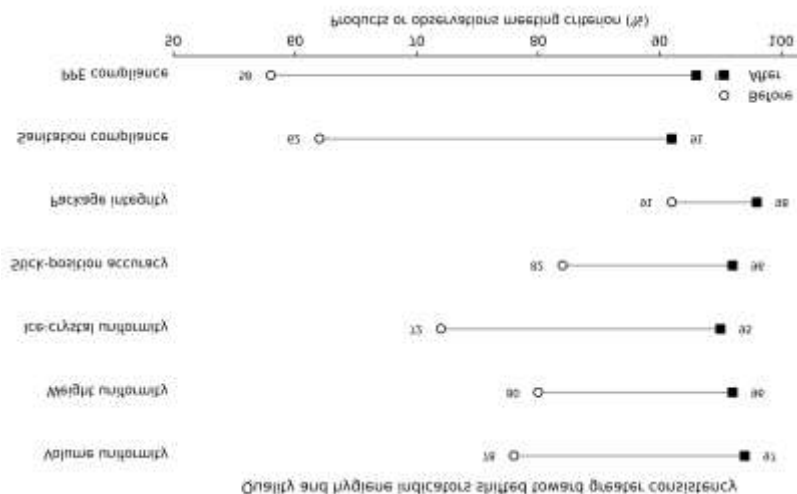


Figure 4. Selected product-quality and hygiene-process indicators before and after MILKONIX.

Values are percentages meeting the corresponding criterion.

Operator competency, standardization, and acceptance

The three trained operators improved from pretest scores of 58, 54, and 56 to post-test scores of 88, 84, and 86. The mean increased from 56 to 86, equivalent to a 30-point absolute and 53.6% relative improvement. Every operator gained exactly 30 points. Practical-skill assessments after training were 92% for machine operation, 90% for executing the production sequence, 93% for sanitation/CIP, 88% for panel and data reading, 86% for routine maintenance, and 84% for minor-fault handling. Operators successfully resolved 17 of 20 simulated minor disturbances without instructor assistance.

Standardization accompanied skill development. Ten SOPs and one quality-assurance manual were implemented, with reported mean compliance of 94.2%. Two internal audits improved from 84% overall compliance at the first audit to 94% at the second. The digital dashboard stored complete data for 10 of 10 monitored batches and supported retrieval of start time, finish time, quantity, temperature deviations, and sanitation status. Thus, process knowledge that had previously resided largely in operator experience was partly externalized into operating parameters, records, and corrective-action routines.

User acceptance was high after the first 10 production batches. The owner and three operators provided an overall mean score of 4.68/5. Usefulness and product-quality improvement were each scored 4.88, production efficiency 4.75, ease of cleaning 4.75, fit with enterprise needs 4.75, and overall satisfaction 4.75. Maintenance received the lowest score, 4.25, despite remaining in the project's 'very good' category. This lower rating is analytically important because sensor calibration, electrical faults, and controller repair still required external technical support. The result identifies maintenance capability and spare-part access as potential constraints on long-term scaling.

Early business translation

Although business outcomes were secondary to the production study, the project recorded substantial early changes after routine use. Monthly production capacity increased from 20,800 to 46,800

sticks under an assumption of 26 working days, while monthly sales volume increased from 18,200 to 39,600 sticks. Unit production cost was reported to decline from IDR 1,350 to IDR 1,120, and gross margin per unit increased from IDR 650 to IDR 880 at an average selling price of IDR 2,000. Active sales points increased from 12 to 28. These observations suggest that operational gains can translate into business opportunity; however, the before-and-after period covered only one month on each side, and market outcomes can be affected by demand, seasonality, promotions, and other factors. They are therefore presented as contextual evidence rather than causal economic effects.

Table 2. Integrated before-and-after performance outcomes.

Outcome	Before	After	Change	Statistical / interpretive note
Active production time	180 min/batch	102 min/batch	−43.3%	10 post-intervention batches; aggregate baseline/post values
Freezing time	150 min	112 min	−25.3%	Within planned 20–30% reduction range
Batch capacity	400 sticks	600 sticks	+50.0%	Throughput increased despite shorter active time
Daily capacity	800 sticks	1,800 sticks	+125.0%	2 to 3 batches day ^{−1}
Labor productivity	200 sticks worker ^{−1} day ^{−1}	600 sticks worker ^{−1} day ^{−1}	+200.0%	4 to 3 direct workers
Cleaning time	45 min	22 min	−51.1%	Partial CIP implemented
Energy per batch	12.8 kWh	10.9 kWh	−14.8%	Slightly below 15% project target
Energy intensity	0.0320 kWh/stick	0.0182 kWh/stick	−43.2%	Calculated from unrounded batch values
Volume uniformity	78%	97%	+19 pp	n=100/condition; Fisher p<0.001 (exploratory)
Weight uniformity	80%	96%	+16 pp	n=100/condition; Fisher p<0.001 (exploratory)
Ice-crystal uniformity	72%	95%	+23 pp	n=100/condition; Fisher p<0.001 (exploratory)
Stick-position accuracy	82%	96%	+14 pp	n=100/condition; Fisher p=0.003 (exploratory)
Package integrity	91%	98%	+7 pp	n=100/condition; Fisher p=0.058
Total defects	9%	2%	−77.8% relative	n=100/condition; Fisher p=0.058
Sanitation compliance	62%	91%	+29 pp	Process-compliance indicator
Manual product contacts	28/batch	6/batch	−78.6%	Observed process-contact frequency
Operator competency	56/100	86/100	+53.6%	n=3; each operator gained 30 points
Partner acceptance	—	4.68/5	—	Owner + 3 operators after 10 batches

Note. pp, percentage points. Product-level Fisher tests are exploratory because the 100 products per condition were drawn from 10 batches and batch-specific clustering information was unavailable. No inferential tests were generated for aggregate-only outcomes.

Integrated automation changed the production system, not only individual tasks

The principal finding is that a compact semi-automated line produced concurrent improvements in time, throughput, labor productivity, product consistency, and hygiene-process control. Active production time fell by 43.3% while batch capacity increased by 50%, yielding a 164.7% increase in active throughput. Similar food-SME studies report directionally comparable gains, including an approximately 39% cycle-time reduction after integrated material handling in an Indonesian snack SME (Anggrahini et al., 2020) and throughput increases of 31.2% and 12.0% in two robotic food-production scenarios (Baek et al., 2024). Although the systems are not directly comparable, they reinforce that automation performance depends on bottleneck structure and process integration rather than on machine speed alone (Heema et al., 2022; Burke et al., 2018).

Integration appears to have reduced both direct work and interface losses. Filling time fell from 70 to 32 min even as batch size increased from 400 to 600 units, indicating benefits from synchronized pumping, conveyor movement, and stick insertion. Task-specific studies similarly show that PLC-based filling and automated wrapping can reduce processing time and inconsistency in small-scale food operations (Mouleeshuwarappabu et al., 2025; Basar et al., 2025). MILKONIX extends this logic across connected operations; cleaning time also fell by more than half because tanks, lines, pumps, and nozzles were treated as one cleaning circuit. The productivity effect therefore reflects reduced waiting, handling, and reconfiguration between unit operations.

The labor result should not be interpreted as simple worker replacement. Direct labor fell from four to three workers, while remaining effort shifted toward preparation, quality checking, packaging, monitoring, and documentation. Collaborative-automation research treats human flexibility and automated efficiency as complementary design resources (Accorsi et al., 2019), and recent food-manufacturing evidence likewise identifies operator skills as a condition for sustainable robotics adoption (Taha, 2026). The 200% increase in output per worker therefore reflects both mechanization and redistribution of work. Longer-term studies should assess workload, ergonomics, task enrichment, and whether higher-skilled responsibilities are matched by appropriate training.

Throughput gains did not require a trade-off in product consistency

A key question in scaling food production is whether higher throughput increases variability. Here, volume uniformity rose from 78% to 97%, weight uniformity from 80% to 96%, and total defects fell from 9% to 2% while batch output increased. This supports the hypothesis that process standardization can decouple output growth from quality deterioration. Controlled mixing, metered filling, synchronized conveying, and controlled freezing provide a plausible mechanism. Food-automation literature consistently identifies precision and repeatability as major benefits (Raffik et al., 2023), while Quality 4.0 research emphasizes that automated quality control is strongest when sensing and verification are embedded in auditable routines (Sánchez-Rodríguez et al., 2025).

The freezing result is particularly relevant to frozen dairy processing. Freezing in batch ice-cream systems depends strongly on heat-transfer conditions and process dynamics (Giudici et al., 2021). MILKONIX reduced freezing time by about one quarter and increased the project-defined crystal-uniformity indicator from 72% to 95%. The study did not directly measure crystal size, so this outcome should not be interpreted as a microstructural measurement. Nevertheless, chamber-temperature stability, shorter freezing time, improved texture scores, and fewer freezing failures are internally consistent with better thermal control. This also accords with the broader principle that intelligent food processing should optimize both quality and resource efficiency at system level (Raut et al., 2022).

The exploratory product-level tests reinforce several changes but also show the limits of the available data. Volume uniformity, weight uniformity, crystal uniformity, and stick-position accuracy all differed clearly in pooled 100-product comparisons. In contrast, the decline in total defects from 9% to 2% yielded $p = 0.058$ under Fisher's exact test. A superficial reading might treat this as 'no effect,' even though the relative reduction was nearly 78%. The more appropriate interpretation is that the direction and magnitude are promising but the sample is insufficient for a precise confirmatory estimate, particularly because the products were nested within batches. Future studies should preserve batch-level raw observations and use mixed-effects or generalized estimating-equation models to account for clustering.

Hygiene gains were achieved through process design and discipline

Milk-based products require a stronger hygiene argument than non-perishable foods because contamination may originate from raw materials or be reintroduced after heating. Prior studies have reported *Bacillus cereus* and other microbial hazards in milk and dairy products (Ahmed et al., 1983; Hassan et al., 2010; Reta et al., 2016; Garbaj et al., 2016). Accordingly, the most defensible hygiene contribution of MILKONIX is a set of process changes that reduce contamination opportunities: closed transfer, fewer manual contacts, controlled pasteurization, structured cleaning, PPE compliance, and sanitation records. Food-automation literature similarly identifies reduced handling and greater process regularity as important hygiene-related benefits (Raffik et al., 2023; Taha, 2026).

Manual product contacts fell by 78.6%, while sanitation compliance rose from 62% to 91%. Partial CIP reduced cleaning time from 45 to 22 min while adherence to the documented cleaning sequence increased. Thus, shorter cleaning did not occur at the expense of procedural discipline. This is consistent with the logic of process control, in which measured states and predefined responses reduce operator-to-operator variability (Adeloju, 2004). In MILKONIX, sanitation became a controlled, documented production step rather than an informal housekeeping activity, an important shift for small enterprises with limited supervisory capacity.

The manuscript intentionally does not use the provisional microbiological values in the project report as confirmatory evidence. That choice is important for scientific integrity. A strong future validation should collect independently verified total plate counts, coliforms, indicator organisms, and relevant pathogens under a pre-specified sampling protocol, with replicate samples linked to specific batches and process conditions. Such data would allow the present process-hygiene improvements to be connected directly to microbiological risk reduction. Until then, the supported conclusion is that MILKONIX improved hygiene-process control, not that it has definitively established a particular magnitude of microbial reduction.

Digital monitoring transformed tacit production into traceable process control

The dashboard changed the management logic of the enterprise by converting transient operator observations into batch-linked process records. Key parameters were logged every 5 s, and records were complete for all 10 monitored batches. Sensor and monitoring research has long emphasized online measurement for process control and quality assurance (Adeloju, 2004; Griffin et al., 2001). More recently, Konur et al. (2023) showed that traditional food production can be modernized with IoT and smart control without wholesale equipment replacement. MILKONIX represents a lower-complexity version of that approach: data capture stabilizes and documents a modest semi-automated line rather than creating a fully autonomous factory.

Digitalization can create new dependency if operators cannot interpret the information generated by the system. MILKONIX therefore coupled the dashboard with training and SOPs; mean operator scores increased from 56 to 86, and all assessed practical competencies exceeded 80%. This supports a socio-technical interpretation in which the effective innovation is the machine plus the users and routines around it. Manufacturing-SME research likewise emphasizes alignment between technology and human-resource capability (L'Écuyer et al., 2019), while automation literature stresses organizational readiness and process fit (Moreira et al., 2024; Santos et al., 2019). Skill development is also highlighted in reviews of digital transformation in food-processing MSMEs (Ranjini et al., 2025).

The maintenance score provides an important counterpoint. Users rated maintenance lower than other acceptance domains, and complex calibration or electrical issues still required external support. This mirrors wider food-manufacturing evidence that skills and SME readiness can constrain robotics adoption despite performance benefits (Taha, 2026). Scalable deployment should therefore include component standardization, spare-parts planning, maintenance logs, fault guidance, and clear service pathways. These are not peripheral features: a system that cannot be maintained predictably will eventually lose the consistency advantages that justified automation.

Energy, economics, and the importance of denominator choice

The energy results illustrate the importance of denominator choice. Batch energy use fell by 14.8%, narrowly missing the project's 15% target, but batch output increased by 50%. Consequently, energy intensity fell from 0.0320 to 0.0182 kWh per stick, a 43.2% reduction. This per-unit measure better reflects resource productivity. The same logic applies to labor, where headcount changed modestly but output per worker tripled. Recent smart-manufacturing work similarly combines process engineering

with digital monitoring of downtime and resource use (Valles et al., 2025), while food-sector analytics research highlights dashboards as tools for operational sustainability decisions (Hassani et al., 2025).

Early business records suggest that technical gains had commercial relevance: monthly sales more than doubled, reported unit cost fell, and gross margin increased. However, these changes cannot be attributed exclusively to MILKONIX because there was no control site and the commercial observation window was short. Demand, promotions, customer acquisition, and seasonality may also contribute. Food-sector digitalization research supports a plausible pathway from technology adoption to SME performance, but emphasizes the mediating role of organizational capability and market context (Mashoko, 2025). A stronger economic study should include several months of data, depreciation, maintenance, payback period, net present value, and sensitivity to utilization and energy prices.

Contribution to small-scale food-processing research

The study contributes an applied model of integrated right-sized automation. MILKONIX occupies an intermediate space between household manual processing and large industrial lines by combining selected automation with human oversight at a 30-L batch scale. Related research shows that collaborative systems can combine human flexibility with automated efficiency (Accorsi et al., 2019), task-specific automation can reduce cycle time in food SMEs (Anggrahini et al., 2020; Basar et al., 2025), and Industry 4.0 functions can improve visibility and consistency without wholesale equipment replacement (Konur et al., 2023). MILKONIX synthesizes these principles in one physical-and-managerial production system.

This integration also argues against framing technology adoption as a binary transition from manual to automatic. The more useful design question is which operations require tight machine control, which benefit from human judgment, and how information should move across the system. Pasteurization temperature and fill volume benefit from repeatable control, while preparation, final packaging, and some maintenance remain operator-dependent. This selective configuration resembles collaborative automation, where human and machine capabilities are complementary (Accorsi et al., 2019), and Quality 4.0 thinking, where sensing and evidence-based verification are embedded within management systems (Sánchez-Rodríguez et al., 2025).

The findings also inform the Industry 4.0 discussion in food systems. For SMEs, practical digitalization may begin with sensors that stabilize critical parameters, batch records that expose deviations, and dashboards that support evidence-based decisions rather than fully autonomous cyber-physical factories. Konur et al. (2023) demonstrated modernization of a traditional food manufacturer through smart control and data services, while Valles et al. (2025) combined conventional industrial engineering with IoT and machine learning to improve production efficiency. Raut et al. (2022) similarly argues for intelligent processing that addresses both product quality and resource efficiency. MILKONIX illustrates a deliberately low-complexity pathway to that objective.

Limitations and research agenda

Several limitations constrain the findings. First, the study involved one enterprise, so effect sizes may depend on the highly manual baseline, local formulation, operator experience, and facility layout. Second, the before-and-after design lacked a concurrent control site, so unrelated temporal changes cannot be excluded. Third, complete batch-level raw data were unavailable for every endpoint, preventing estimation of batch-to-batch variance and multivariable modeling. Fourth, MILKONIX was a multi-component intervention, so the design estimates the integrated package rather than the marginal effect of each module. This matters because food-automation effects vary with process configuration and baseline bottlenecks (Baek et al., 2024; Valles et al., 2025).

Further limitations concern outcome measurement. Product-quality data pooled 100 units per condition from 10 batches without reporting within-batch correlation, so Fisher tests are exploratory. Sensory outcomes were summarized without individual-level data or detailed instrument validation. Most importantly, microbiological values in the source report were explicitly marked as provisional and were excluded from confirmatory claims. Thus, the study demonstrates improved hygiene-process control but not a verified magnitude of microbial-risk reduction. Business outcomes were also observed over short periods and cannot establish causal financial returns. These boundaries are necessary to avoid overstating the evidence.

Future research should use a multi-site prospective design with predefined outcomes, raw batch-level data, and repeated measurement over several months. Engineering evaluation should include cycle-time distributions, downtime, OEE, energy intensity, and maintenance events; product evaluation should

include replicated volume, mass, instrumental texture, freezing curves, and independently verified microbiology; and organizational evaluation should include workload, acceptance, cost of ownership, return on investment, and market absorption. A stepped-wedge or matched-enterprise design could be practical when randomization is difficult. Retaining batch-linked digital records would also enable hierarchical analysis and more auditable quality evaluation (Sánchez-Rodríguez et al., 2025).

A further priority is to identify the minimum effective automation package. Factorial pilots or staged module introduction could estimate the marginal contribution of controlled mixing, precision filling, freezing, CIP, and digital monitoring. Such evidence would help SMEs prioritize investment under capital constraints, a recurring issue in food-automation adoption (Accorsi et al., 2019; Baek et al., 2024). Maintenance burden should be analyzed alongside productivity because component availability, calibration requirements, and technical support may determine whether gains persist after project support ends. The broader goal is to move from case-based technology demonstrations toward transferable design rules for right-sized food automation.

Taken together, the evidence supports the thesis that productivity transformation in small food enterprises is not driven by machine speed alone. The largest gains arose because formerly disconnected operations became a coordinated system with defined parameters, fewer manual interfaces, documented sanitation, trained users, and traceable data. This interpretation is consistent with socio-technical perspectives in manufacturing SMEs (L'Écuyer et al., 2019) and food-sector digitalization research emphasizing technology, skills, and operational integration (Ranjini et al., 2025; Taha, 2026). MILKONIX therefore provides a testable example of integrated socio-technical automation. Its effect sizes justify broader validation, but the single-site design means the contribution is a bounded systems model rather than a universal causal claim.

CONCLUSION

MILKONIX transformed a fragmented manual milk-ice production process into a compact semi-automated line that integrated pasteurization, controlled mixing, precision filling, stick insertion, freezing, partial CIP, and digital monitoring. Active production time decreased by 43.3%, batch capacity increased by 50%, daily capacity increased by 125%, and labor productivity increased by 200%. At the same time, volume uniformity increased from 78% to 97%, total defects fell from 9% to 2%, cleaning time decreased by 51.1%, and sanitation compliance increased from 62% to 91%. Operator competency improved by 53.6%, indicating that the performance gain was supported by human-capability development rather than equipment alone.

The evidence supports a systems-level conclusion: appropriately scaled automation can improve throughput and product consistency simultaneously when process integration, hygienic practice, digital traceability, SOPs, and operator training are treated as a single intervention. The study does not establish population-level causality because it involved one enterprise, a short evaluation period, and incomplete batch-level raw data. Microbiological claims also require independent laboratory confirmation. Nevertheless, MILKONIX provides a testable model of integrated socio-technical automation for small food enterprises. Replication across multiple SMEs with longer follow-up, validated microbiological testing, full batch-level datasets, and economic analysis is the logical next step.

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