

Gyozenova Smart Automation Improves Gyoza Production Efficiency and Standardization in a Food Microenterprise

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ABSTRACT

Penelitian ini mengevaluasi Gyozenova, sistem produksi dumpling otomatis cerdas terintegrasi, untuk meningkatkan produktivitas, konsistensi produk, higiene proses, kemampuan operator, dan visibilitas data pada UMKM pangan di Indonesia. Evaluasi menggunakan desain lapangan sebelum-sesudah yang mencakup fungsi mesin, efisiensi produksi, standardisasi produk, kepatuhan higiene, hasil pelatihan, penerimaan teknologi, dan kinerja operasional-ekonomi. Kapasitas stabil meningkat dari 300 menjadi 450 gyoza per jam, waktu produksi per batch turun dari 120 menjadi 80 menit, dan produktivitas tenaga kerja meningkat dua kali lipat dari 75 menjadi 150 unit per orang-jam. Koefisien variasi berat produk turun dari 9,8% menjadi 3,7%, tingkat cacat dari 6,7% menjadi 1,6%, dan kesesuaian produk mencapai 98,4%. Titik kontak tangan berkurang 64,3%, ketidaksesuaian higiene 70,0%, dan kepatuhan sanitasi mencapai 94,0%. Hasil menunjukkan bahwa otomasi skala UMKM paling efektif ketika integrasi mekanis disertai standardisasi prosedur, pelatihan operator, disiplin sanitasi, pemeliharaan preventif, dan pemantauan digital rutin dalam kondisi produksi nyata lokal dengan sumber daya terbatas.

This study evaluated Gyozenova, an integrated smart automated dumpling production system, for improving productivity, product consistency, hygiene processes, operator capability, and data visibility in an Indonesian food microenterprise. A pragmatic before-after field design assessed machine functionality, production efficiency, product standardization, hygiene compliance, training outcomes, technology acceptance, and operational economics. Stable capacity increased from 300 to 450 dumplings per hour, while batch time decreased from 120 to 80 minutes and labor productivity doubled from 75 to 150 dumplings per worker-hour. Product-weight coefficient of variation decreased from 9.8% to 3.7%, defects fell from 6.7% to 1.6%, and overall conformance reached 98.4%. Direct hand-contact points decreased by 64.3%, hygiene nonconformities by 70.0%, and sanitation-procedure compliance reached 94.0%. The findings showed that appropriately scaled automation was most effective when mechanical integration was combined with standardized procedures, operator training, sanitation discipline, preventive maintenance, and routine digital monitoring for resource-constrained food SMEs under real production conditions



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INTRODUCTION

Micro and small food enterprises occupy an important position in local food systems because they can respond quickly to changing consumer preferences, produce culturally specific foods, and create employment with relatively modest capital requirements. Their production systems, however, are often built around manual skills rather than engineered process control. This arrangement is flexible at low volume but becomes increasingly restrictive when demand rises. Repetitive filling, shaping, folding, portioning, and transfer operations can create bottlenecks; output becomes strongly dependent on

individual operator speed; and quality differences accumulate across workers and batches. In such settings, scaling up is not simply a matter of adding labor. Additional workers may increase coordination needs, space requirements, hygiene risks, and production variability (Bakare et al., 2024; Ibrahim, 2023).

The challenge is especially visible in foods such as dumplings and gyoza, where product quality depends on simultaneous control of wrapper characteristics, filling mass, filling position, closure pressure, fold geometry, and transfer after forming. A manual process can produce visually acceptable products, but it typically relies on tacit operator skill. When demand increases, the enterprise must maintain product identity while preventing wider variation in weight, size, appearance, and sealing integrity. The source project at Ikhana Kitchen illustrates this problem. Baseline production was conducted with simple kitchen equipment and intensive manual handling. Average throughput was 300 gyoza h⁻¹, a 600-unit batch required approximately 120 min, and four workers were directly involved in preparation, filling, forming, folding, and tray arrangement. Work-in-process accumulated around the filling and forming stages, while output depended heavily on worker speed and endurance.

Automation is a potential response, but the transfer of industrial automation concepts to food microenterprises is not straightforward. Research cited in the project report emphasizes that small and medium enterprises face barriers associated with investment, workforce capability, process readiness, and the integration of digital technologies into existing operations (Alsaadi, 2024; Dossou et al., 2022). Food operations impose additional requirements because machinery must not only be productive but also cleanable, food-compatible, safe to operate, and sufficiently adaptable to variable biological materials. Reviews of robotics, Industry 4.0, and food-quality management further suggest that the value of automation arises from the combination of physical automation, sensing or data capture, standardized procedures, and human capability rather than from machine speed alone (Duong et al., 2020; Peres et al., 2025).

Evidence from food-processing automation supports both the opportunity and the constraints underlying this intervention. Collaborative automation has been proposed as a way to combine human flexibility with machine efficiency in food production, particularly where conventional automation is constrained by low margins, heterogeneous products, and the prevalence of SMEs (Accorsi et al., 2019). Simulation and field validation in home-meal-replacement loading showed throughput gains of 31.2% in a large-scale case and 12.0% in an order-based case, with one worker able to operate the robotic system (Baek et al., 2024). An overview of robotics in food industries likewise identifies productivity and hygiene as important benefits while noting potential workforce and skill consequences (Raffik et al., 2023). At smaller scales, an Indonesian food-SME case using karakuri-supported automation reduced cycle time by about 39% (Anggrahini et al., 2020), whereas an automated wrapper for roasted glutinous rice shortened wrapping time by 4.22 s per item while improving consistency (Basar et al., 2025). Recent Malaysian evidence further links robotics adoption with economic, environmental, and social performance, but emphasizes implementation cost, operator skills, and SME readiness as persistent barriers (Taha, 2026).

This distinction is important for microenterprise research. A machine can increase nominal capacity while failing to generate practical value if defect rates rise, cleaning becomes burdensome, operators cannot maintain the equipment, or production data remain invisible to management. Conversely, modest automation may create substantial value when it stabilizes a critical bottleneck, reduces direct handling, makes parameters repeatable, and creates a basis for standard operating procedures and monitoring. For this reason, the present study treats automation as a socio-technical intervention rather than as an isolated piece of equipment. The Gyozenova system combines mechanical automation with operator training, sanitation procedures, product standards, preventive maintenance, and a simple digital production dashboard.

The literature therefore increasingly treats food-SME modernization as a readiness and organizational problem rather than a hardware-purchase decision. In West Java, business-ecosystem conditions and digital transformation were positively associated with the success of small culinary firms (Abdul Wahab et al., 2024), while an ISM-MICMAC study identified interacting enablers that shape digital transformation in food SMEs (Chandrayan et al., 2023). Reviews of Industry 4.0 maturity models show that most frameworks were designed for larger organizations and require adaptation to the financial and human-resource constraints of food SMEs (Arena et al., 2023). Empirical assessment of seafood-processing SMEs similarly found that many firms still operate mainly with Industry 1.0-3.0 practices,

despite comparatively greater readiness in business processes, documentation, and communication (Madhavan et al., 2024). Proposed Industry 5.0 models for food SMEs consequently emphasize tailored and staged transition pathways rather than abrupt technology replacement (Saptaningtyas & Rahayu, 2020). Broader reviews also stress that Industry 4.0 benefits in agri-food systems coexist with challenges of social adaptability, trust, and resource constraints (Yap & Al-Mutairi, 2024), while digital platforms have already demonstrated value for MSME continuity and local-food-system resilience (Musa et al., 2023).

The specific case is Ikhana Kitchen, a micro and small food enterprise located in Merjosari, Malang, Indonesia, producing handmade gyoza for ready-to-eat and frozen markets. Prior to the intervention, the enterprise faced four linked constraints. First, filling and forming were labor-intensive and limited throughput. Second, product weight and geometry were inconsistent. Baseline measurement of 100 randomly selected products gave a mean mass of 22.6 g with a standard deviation of 2.22 g and a coefficient of variation of 9.8%. Third, quality losses were material: approximately 6.7% of a 600-unit batch was classified as defective because of incomplete folds, filling leakage, torn wrappers, or weight outside the internal specification. Fourth, production management relied on manual records that did not systematically capture defects, downtime, sanitation, material utilization, or maintenance.

These constraints define a research gap that is broader than the local case. Much of the practical discussion around small-scale automation focuses on whether a device functions or whether output rises. Less attention is paid to whether higher throughput is accompanied by lower variation, lower defect generation, improved process hygiene, increased operator competence, and better managerial visibility. For craft-based food production, this multidimensional question is central because scaling is valuable only when the process remains stable and controllable. The key issue is therefore not simply whether a dumpling machine can form products, but whether appropriately scaled automation can transform a worker-dependent production process into a parameter-controlled and data-visible system.

A second strand of evidence concerns the data infrastructure required to convert mechanization into smart production. A real-world food-manufacturing case showed that legacy machinery can be adapted rather than completely replaced when smart production control, data collection, and intelligent monitoring are layered onto existing operations (Konur et al., 2023). More recent field work argues that the critical SME bottleneck can be the operational data foundation itself: continuity, interpretable semantics, diagnosability, and maintainability are prerequisites for later analytics (Kang & Park, 2026). Lean-Industry 4.0 models for food SMEs likewise combine productivity improvement with forecasting, decision support, and visual analytics (Komori-Zevallos et al., 2023). In a medium-scale bakery, a digital-twin architecture reduced cycle time by 24.4% and inter-operational waiting time by 51.2% during validation (Amirkhanova et al., 2026), while an integrated smart-manufacturing model for snack production combined line balancing, predictive maintenance, IoT, and machine learning to improve production efficiency (Valles et al., 2025). Such findings support hybrid, stepwise modernization strategies for traditional SMEs rather than an all-or-nothing Industry 4.0 transition (Wang et al., 2021).

Gyozenova was developed to address this problem. The system integrates separate dough and filling hoppers, metered delivery, a stainless-steel cladding forming die, a food-grade conveyor, an electric drive with speed control, an emergency-stop system, and removable food-contact components. The design was adapted to the spatial and operational constraints of the partner enterprise through iterative testing and operator feedback, an approach consistent with user-oriented equipment development for small food businesses (Putra & Putri, 2025). The intervention also established target settings for production rate, filling pressure, wrapper thickness, cleaning, sampling, and corrective action.

Accordingly, this study aimed to evaluate the technical and operational performance of Gyozenova under real production conditions. The primary hypothesis was that integrated automation would increase throughput and labor productivity while reducing cycle time, manual handling, product variability, and defect generation. Secondary hypotheses were that the intervention would improve process-hygiene compliance, increase operator competence and technology acceptance, and strengthen production monitoring and unit economics. The intended scientific contribution is an empirically grounded model of “appropriate smart automation” for a food microenterprise: a system in which mechanical integration, standardization, human capability, and simple digital monitoring operate together to improve production performance.

The manuscript therefore advances a specific systems-level argument: for resource-constrained food microenterprises, the relevant outcome of automation is not maximum machine speed but stable saleable throughput generated by the joint control of material flow, product variation, operator practice, sanitation, and production data. This framing differentiates Gyozenova from a stand-alone equipment demonstration and makes the case transferable to other craft-based foods that combine portioning, filling, forming, and repetitive manual handling.

METHOD

Study setting and evaluation design

The study was conducted at Ikhana Kitchen in Merjosari, Malang, East Java, Indonesia. The enterprise produces gyoza using dough wrappers and prepared fillings in a compact production area. The evaluation used a pragmatic before-after field design. Baseline measurements represented the established manual process, whereas post-intervention measurements were obtained after functional testing, installation, operator training, parameter adjustment, and routine use of Gyozenova. The intervention was therefore evaluated as an integrated production-system change rather than as a laboratory test of a single mechanical component.

The implementation sequence comprised six stages: needs assessment, collaborative system design, pilot testing, workflow integration, full implementation with management-system strengthening, and post-implementation monitoring. Direct observation, interviews with the owner and operators, time-and-motion measurements, production records, product measurements, hygiene checklists, training tests, and technology-acceptance questionnaires were used. The enterprise provided access to the production area, materials, workers, routine production data, and product samples.

Gyozenova system configuration

Gyozenova was constructed as a compact automated dumpling forming system with overall dimensions of approximately 120 × 65 × 135 cm and a mass of about 128 kg. Food-contact and external structural surfaces were fabricated principally from SUS 304 stainless steel. The system included two separate hoppers: an 8-kg dough hopper and a 6-kg filling hopper. A 1-hp, 220-V electric motor coupled to a 1:30 gearbox supplied the mechanical drive. The control panel provided start, stop, speed adjustment, power indication, and emergency-stop functions.

The forming unit used an 80-mm working-diameter cladding forming die. The target final mass was 22.5 g per piece, with an intended product length of approximately 75 mm and width of approximately 38 mm. Formed products were transferred using a food-grade conveyor approximately 80 cm long and 20 cm wide. Production speed could be adjusted nominally from 350 to 500 units h⁻¹. The machine was mounted on lockable casters to allow repositioning within the limited production room.

Design modification was performed with operator input. The hopper height was lowered by approximately 12 cm from the initial design, and the control panel was repositioned to improve reach. Guards, an emergency-stop device, and accessible removable components were incorporated to improve safety and cleaning. At the enterprise, the preparation table was moved by 1.2 m and an 80-cm clear zone was maintained around the machine to support access, inspection, disassembly, and sanitation. Figure 1 summarizes the integrated production architecture and the supporting management elements.

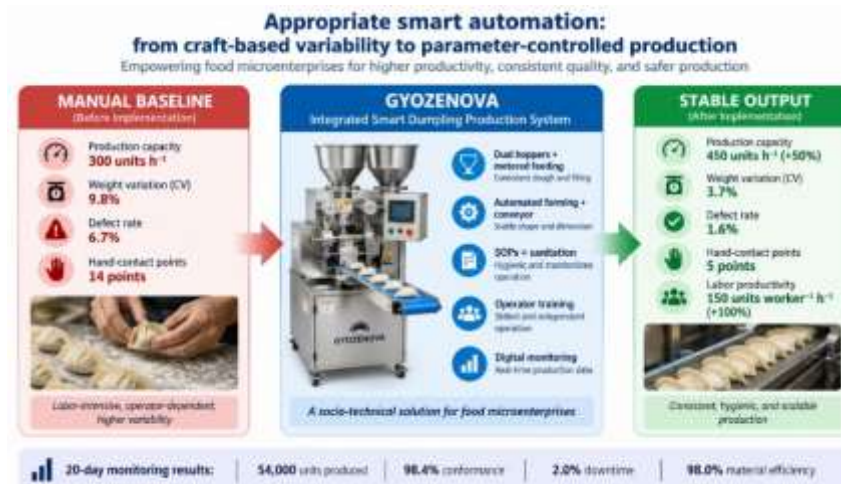


Figure 1. Gyozenova socio-technical production architecture. Mechanical automation is integrated with SOP-based operation, sanitation, operator training, preventive maintenance, and digital monitoring.

Functional testing and operating conditions

Functional testing was conducted before full integration. Three 60-min operating cycles were performed at nominal settings of 350, 425, and 500 units h⁻¹. The assessment covered motor and gearbox stability, panel function, emergency stopping, material flow, forming performance, conveyor transfer, electrical integrity, product weight, and component disassembly. Motor speed fluctuation, frame vibration, and motor temperature were observed during operation. The start-stop functions were tested 30 times, whereas the emergency stop was tested 10 times.

Initial tests revealed variability in filling delivery and required calibration of the pusher position, feed opening, die alignment, and conveyor speed. After adjustment, filling deviation was reduced to approximately ± 0.6 g. Full implementation began at 350 units h⁻¹ to permit operator adaptation, after which speed was increased stepwise to 400, 450, and 500 units h⁻¹. The 450-unit h⁻¹ setting was selected as the stable routine condition because it provided a practical balance between throughput and consistency for the dough and filling characteristics used by Ikhana Kitchen. At this setting, conveyor speed was approximately 3.6 m min⁻¹, filling pressure was set to level 4 of 6, and wrapper thickness was approximately 1.4 mm.

Standardization, training, and digital monitoring

The technological intervention was accompanied by a structured standardization package. Standard operating procedures covered ingredient preparation, machine start-up and operation, weight and speed adjustment, shutdown, cleaning and sanitation, minor troubleshooting, occupational safety, product standardization, quality inspection, preventive maintenance, and production recording. Ingredient preparation specified a 12-min mixing period and a 20-min dough-resting period. Product inspection used an internal target mass range of 21.5–23.5 g, length of 73–77 mm, width of 36–40 mm, and a fully closed fold.

Four participants—three production operators and the enterprise owner—completed four training sessions with a total duration of 16 h. Training combined explanation, demonstration, guided practice, independent operation, sanitation, basic troubleshooting, quality control, preventive maintenance, and data recording. Knowledge was assessed using a 25-item test and practical competence using a 20-indicator observation sheet. The competency threshold was set at 80 points.

A spreadsheet-based production dashboard was introduced to record daily output, conforming and defective products, process time, downtime, material use, sanitation, preventive maintenance, incoming orders, inventory, and corrective actions. Operators entered production and machine data, and the owner verified records at the end of each production day. The monitoring period reported here covered 20 production days.

Outcome definitions and data collection

Production efficiency was evaluated using hourly capacity, time required for a 600-unit batch, manual handling time per batch, labor productivity, process waiting time, daily output, order-fulfilment

rate, material-use efficiency, and number of workers directly engaged in forming operations. Labor productivity was calculated as hourly output divided by the number of directly engaged workers.

Product standardization was evaluated using mass, dimensional conformity, filling accuracy, fold and shape uniformity, total conformance, and defect frequency. The baseline weight analysis used 100 randomly selected manually produced gyoza. Post-intervention weight evaluation used 300 products sampled from multiple production batches. Reported metrics included mean, minimum, maximum, standard deviation, and coefficient of variation. The coefficient of variation was calculated as the standard deviation divided by the mean and multiplied by 100. Defects were classified as torn wrapper, filling leakage, incomplete fold or asymmetric shape, and mass outside the internal standard. The baseline defect assessment used a 600-unit batch; the fully implemented process assessment used 300 inspected products.

The first five on-site trial batches each produced approximately 450 units. Batch-level numbers of nonconforming products were 15, 11, 9, 8, and 7, respectively. These data were retained to characterize the learning and calibration phase.

Process hygiene was assessed using direct hand-contact points per 600-unit batch, sanitation-SOP compliance, personal-protective-equipment compliance, hygiene nonconformities, equipment-cleanliness score, sanitation-record completeness, GMP/HACCP-check compliance, scheduled-cleaning completion, and separation of raw materials from finished products. These indicators reflect process hygiene and management compliance; no microbiological enumeration was performed.

Operator capability was assessed using pre- and post-training scores. Technology acceptance was assessed after 20 production days using 18 Likert-scale statements scored from 1 to 5. Nine summary dimensions were reported, including ease of operation, production fit, cleanability, safety, productivity benefit, consistency benefit, maintainability, intention to continue use, and overall satisfaction.

Economic indicators included reported unit production cost, direct production-labor allocation, daily output, saleable output, material efficiency, order fulfilment, potential revenue at the stated selling price of IDR 4,000 per unit, gross profit per unit, and gross margin. These figures represent operational accounting estimates reported by the enterprise and should not be interpreted as independently audited financial statements.

Statistical analysis

The primary analysis was descriptive because the project used a single-site before-after implementation design and much of the source dataset consisted of operational summaries rather than individual-level raw observations. Absolute differences, percentage changes, percentage-point changes, coefficients of variation, and defect proportions were calculated from the reported measurements.

Where sample sizes and summary statistics permitted, exploratory inferential analyses were added to characterize the magnitude of change. A summary-statistics Welch test compared mean product mass before and after implementation, recognizing that the scientific objective was maintenance of the target mean rather than a shift in mean mass. An F ratio was used as an exploratory test of the reported weight-variance reduction; because such tests are sensitive to non-normality and raw distributions were unavailable, this result was interpreted cautiously. A two-sample proportion test compared the reported baseline and post-implementation defect rates, and the corresponding post-versus-pre relative risk was calculated with a 95% confidence interval. A binomial generalized linear trend model was fitted to the five pilot batches to explore whether nonconformity declined systematically with batch number. Paired pre-post training scores for the four participants were analyzed descriptively and with an exploratory paired t test. Given the small sample and non-randomized design, p values are presented as supportive rather than causal evidence. Analyses were performed from the numerical values reported in the source project dataset. The system specifications and evaluation framework are summarized in Table 1.

Table 1. Gyozenova System Specification and Evaluation Framework

Domain	Component / variable	Specification or definition	Evaluation basis
Mechanical	Drive and structure	1 hp; 220 V; 1:30 gearbox; SUS 304; 120 × 65 × 135 cm	180-min functional testing

Domain	Component / variable	Specification or definition	Evaluation basis
Feeding	Dual hoppers	8-kg dough hopper; 6-kg filling hopper	Flow stability and fill deviation
Forming	Cladding forming die	80-mm working diameter; target product mass 22.5 g	Weight, dimensions, folds, defects
Transfer	Food-grade conveyor	80 × 20 cm; routine setting ~3.6 m min ⁻¹	Transfer continuity and product spacing
Control	Panel and emergency stop	Start/stop, speed control, indicator, emergency stop	30 start-stop and 10 emergency-stop tests
Productivity	Stable operating output	Routine setting 450 units h ⁻¹ ; nominal maximum 500 units h ⁻¹	Before-after production measurements
Quality	Internal conformance criteria	21.5-23.5 g; 73-77 mm length; 36-40 mm width; closed fold	100 baseline and 300 post weight samples; defect inspection
Human system	Training and SOPs	4 participants; 16 h training; 11 SOPs	Pre-post scores, practice, acceptance
Digital system	Production dashboard	Output, defects, downtime, materials, sanitation, maintenance, orders, inventory	20 production days

RESULTS AND DISCUSSION

Functional performance, stabilization, and system integration

The completed Gyozenova unit fulfilled the primary mechanical and control functions required for routine gyoza production. Across 180 min of functional testing, the 1-hp drive and 1:30 gearbox operated without reported jamming, abnormal sound, or loss of drive. Output-shaft speed increased with the production setting and showed a reported fluctuation of approximately $\pm 1.8\%$, below the project criterion of $\pm 5\%$. Mean frame vibration was approximately 2.6 mm s⁻¹. Motor temperature increased from 29.4°C at the start of testing to 46.8°C after 60 min, with no reported interruption or electrical fault.

The control system performed consistently. All 30 start-stop tests were successful, and each of 10 emergency-stop tests interrupted power. Mean stopping time after emergency activation was approximately 1.4 s. Electrical inspection over the 180-min test period did not identify short circuits, loose cabling, or overcurrent events. These results supported transfer from component testing to on-site production trials.

Material feeding required calibration before stable operation was achieved. Initial filling imbalance was approximately ± 2.1 g, but adjustment of the pusher and feed opening reduced this to approximately ± 0.6 g. During the final functional test, 300 products had a reported mean mass of 22.5 g and standard deviation of 0.92 g, corresponding to a coefficient of variation of 4.1%. The forming unit produced 294 conforming products among 300 tested, giving a functional-test forming success of 98.0%. The six nonconforming items comprised three filling leaks, two incomplete folds, and one torn wrapper.

The conveyor transferred all 300 tested products without loss from the belt. A small number shifted position but were not damaged. Food-contact components could be removed in a mean of 11.6 min and reinstalled in 13.4 min. These functional results indicated that the machine had sufficient mechanical stability, control reliability, forming accuracy, and cleanability to proceed to routine use.

On-site stabilization required both parameter adjustment and operator learning. During the first five 450-unit trial batches, nonconforming products decreased sequentially from 15 to 11, 9, 8, and 7. This corresponds to a decline in batch defect rate from 3.33% to 1.56%. A binomial trend model indicated a negative association between batch sequence and nonconformity (log-odds slope -0.197 per batch), although the trend was borderline under conventional significance criteria ($p = 0.057$). The pattern is therefore best interpreted as descriptive evidence of stabilization rather than as a definitive learning-effect estimate (Figure 2).

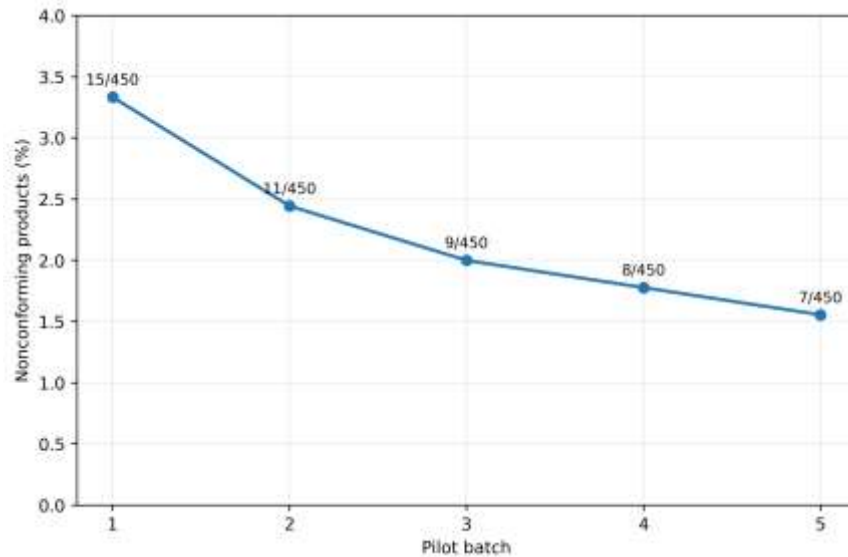


Figure 2. Stabilization during the first five on-site pilot batches. Labels show the number of nonconforming products among 450 units in each batch.

The central finding of this study is that the value of Gyozenova was not limited to an increase in machine speed. The intervention changed the structure of the production system. Filling, forming, folding, and transfer were converted from worker-dependent sequential activities into a synchronized mechanical flow; standard operating procedures made key settings explicit; operators were trained to maintain these settings; and a digital dashboard created visibility of defects, downtime, sanitation, maintenance, inventory, and orders. The observed performance gains therefore emerged from an integrated socio-technical change.

This interpretation is consistent with the broader Industry 4.0 and SME literature cited in the source project. Dossou et al. (2022) emphasize structured approaches to sustainable Industry 4.0 adoption in SMEs, while Peres et al. (2025) frame modern food quality management as an interaction among process control, data, and digital technologies. Zhang et al. (2022) similarly identify organizational and implementation factors as important to successful SME digital transformation. In the present case, the automation hardware created repeatability, but the repeatability became operationally useful only when ingredient preparation, machine settings, inspection criteria, sanitation, and maintenance were codified.

The distinction between nominal and stable capacity illustrates the point. Gyozenova was mechanically capable of producing up to 500 units h^{-1} , but 450 units h^{-1} was selected for routine operation because it provided a more robust balance between material behavior, forming quality, and operator control. This is an important engineering outcome. For a microenterprise, the maximum rated speed is not necessarily the economically optimal speed. A slightly lower setting can produce greater effective output when it reduces interruptions and nonconformity. The relevant performance objective is therefore stable saleable throughput rather than maximum instantaneous throughput.

The Gyozenova findings also clarify where basic automation sits on the broader continuum of food-process control. Distributed control systems were historically introduced to make flexible process control accessible to smaller and batch-oriented food operations (Dahm & Mathur, 1990), and online process analysis has long been framed as a means of linking real-time measurements to corrective control actions (Adeloju, 2004). Specific sensing work, such as ultrasound-based monitoring of filling operations, illustrates the continuing search for non-contact methods that can function at industrial speed

(Griffin et al., 2001). More recent quality-control research has moved toward digital, hyperspectral, and near-infrared imaging with deep learning, reporting classification accuracy above 88% in several agri-food commodities under semi-industrial conveyor conditions (Sánchez-Rodríguez et al., 2025). Deep-learning approaches have also been proposed for rapid fruit classification and grading where manual inspection is slow and inconsistent (Sravanthi et al., 2024). Gyozenova currently occupies an earlier but operationally appropriate stage: it stabilizes the physical process and creates reliable production records before advanced sensing is added.

Production efficiency and product stability

Implementation of Gyozenova changed the production constraint at the forming stage. Stable operating capacity increased from 300 to 450 units h⁻¹, a 50.0% improvement. The machine could operate at 500 units h⁻¹ under functional testing, but 450 units h⁻¹ was selected for routine production because material flow and product quality were more stable at that setting.

For a 600-unit batch, mean production time decreased from 120 to 80 min, representing a 33.3% reduction. Manual handling time decreased from 108 to 54 min per batch, a 50.0% reduction. The effect was particularly important at the filling, forming, and folding stages, which were integrated within the machine rather than performed sequentially by hand.

Direct labor allocation to the main forming flow decreased from four workers to three operators. One operator was assigned to material preparation, one to machine operation, and one to inspection and tray arrangement. The fourth worker could be reassigned to preparation, packaging, recording, or order fulfilment rather than being removed from the enterprise. Because hourly output increased while the number of directly engaged workers decreased, labor productivity increased from 75 to 150 units worker⁻¹ h⁻¹, equivalent to a 100% improvement.

Process waiting time also decreased, from approximately 22 to 7 min per batch, a reduction of 68.2%. The synchronized feed-form-transfer sequence reduced accumulation between filling and folding, and the revised room layout shortened product and material movement. Over a six-hour effective production day, output capacity increased from 1,800 to 2,700 units. Reported order fulfilment increased from 78.0% to 96.0%, whereas material-use efficiency increased from 93.3% to 98.0%. Together, these results show that the intervention affected not only machine cycle rate but also line flow, labor allocation, and conversion of ingredients into saleable product. The magnitude of the principal operational changes is summarized in Table 2 and Figure 3.

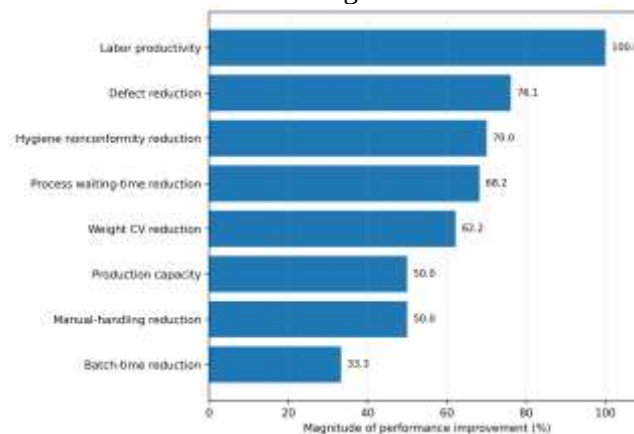


Figure 3. Magnitude of improvement in selected performance indicators after Gyozenova implementation. Reductions in time, variability, defects, and hygiene nonconformities are displayed as positive improvement magnitudes.

A principal requirement of the intervention was that higher throughput should not be achieved at the expense of portion control. Mean product mass remained effectively unchanged: the baseline mean was 22.6 g and the post-implementation mean was 22.5 g. An exploratory Welch test based on the reported means, standard deviations, and sample sizes found no evidence of a mean shift ($t = 0.44$, approximate $df = 108.4$, $p = 0.661$). This is a desirable result because the intervention target was to maintain the approximately 22.5-g portion while reducing variability.

The change in dispersion was much larger. Baseline mass ranged from 18.9 to 26.8 g, with a standard deviation of 2.22 g and coefficient of variation of 9.8%. After implementation, the reported

range narrowed to 21.1-23.9 g, standard deviation decreased to 0.83 g, and the coefficient of variation fell to 3.7% (Figure 4). The standard-deviation ratio indicates that baseline dispersion was approximately 2.7 times the post-implementation dispersion. An exploratory variance-ratio test based on the reported summary statistics gave $F = 7.15$ and $p < 0.001$. Because individual observations were not available for distributional checks, the test should be interpreted as supportive evidence; the descriptive reduction in range, standard deviation, and coefficient of variation provides the more robust practical result.

Dimensional and visual conformity improved in parallel with mass stability. Products meeting the stated dimensional standard increased from 84.0% to 98.7%, whereas uniformity of shape and folds increased from 82.5% to 98.4%. Filling accuracy increased from 86.0% to 98.7%. During full implementation, 295 of 300 inspected products met all recorded standards, corresponding to 98.4% overall conformance.

The total defect rate fell from 6.7% at baseline (40 defects among 600 products) to 1.6% in the full implementation sample (5 defects among 300 products). A two-sample proportion test indicated that this reduction was unlikely to be explained by sampling fluctuation alone under the test assumptions ($z = 3.24$, $p = 0.0012$). The estimated post-versus-pre relative risk of a defect was 0.25 (95% CI approximately 0.10-0.63), equivalent to an estimated 75% relative risk reduction. This statistical estimate is consistent with the reported 76.1% relative decrease calculated directly from the rounded defect percentages.

All major defect categories decreased. Torn wrappers declined from 1.3% to 0.3%, filling leakage from 1.8% to 0.3%, incomplete folds/asymmetric forms from 2.5% to 0.7%, and out-of-standard mass from 1.1% to 0.3%. Process observations indicated that the remaining defects were associated mainly with variation in dough moisture, temporary filling-pressure instability, die cleanliness, or product positioning. The establishment of a 12-min mixing period, 20-min dough rest, level-4 filling pressure, and periodic die cleaning was associated with the final stable condition.

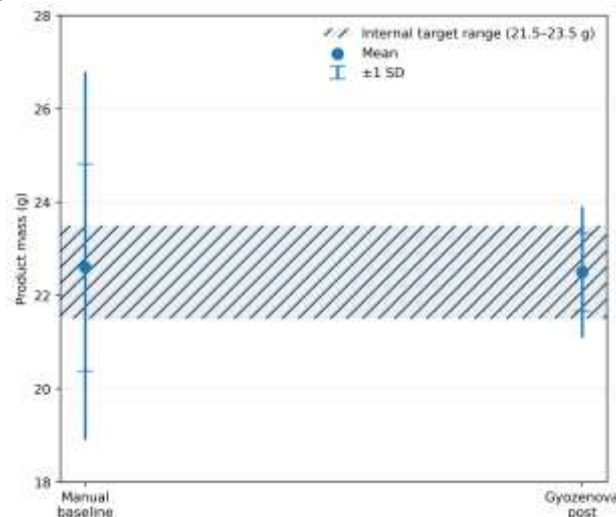


Figure 4. Product-mass stability before and after Gyozenova implementation. Points show means, bars ± 1 SD, vertical lines the min-max range, and the hatched band the 21.5-23.5 g target.

A particularly important result was the combination of higher production rate and lower product variability. Throughput increased by 50%, while the coefficient of variation in mass decreased from 9.8% to 3.7% and the defect rate fell from 6.7% to 1.6%. These changes suggest that Gyozenova broke the usual dependence of manual craft production on operator-specific portioning and folding behavior.

The mean mass remained essentially unchanged at the intended 22.5-g level, while dispersion decreased sharply. This pattern is more informative than a simple change in average. In portion-controlled foods, a stable mean can conceal substantial over- and under-filling. Wide variation creates simultaneous quality and cost problems: under-filled products risk customer dissatisfaction, whereas over-filled products consume ingredients without generating additional revenue. The narrower post-implementation range therefore has both quality and resource implications.

The defect analysis supports the same mechanism. All major defect categories decreased, but the largest relative reduction occurred in filling leakage. Manual filling relies on visual estimation and

operator placement; the automated metering mechanism reduced variation in both volume and position. Incomplete folds also decreased substantially after die alignment, dough-condition standardization, and regular die cleaning. These observations indicate that automation did not eliminate the importance of raw-material properties. Instead, it shifted the dominant control problem from hand-skill variation toward measurable process parameters such as dough consistency, fill pressure, die condition, and conveyor synchronization.

This shift is scientifically relevant because it changes the nature of process improvement. Worker-dependent systems are difficult to standardize because performance resides partly in tacit skill. Parameter-controlled systems can be monitored, adjusted, and transferred more readily. Samáková et al. (2025), as cited in the project report, link standardization and equipment capacity to process-flow optimization. The present field results illustrate this relationship at microenterprise scale: stable product geometry and reduced variation were achieved through the combination of fixed forming geometry, controlled filling, standardized dough preparation, and synchronized transfer.

The simultaneous 50% increase in stable throughput and 62.2% reduction in weight coefficient of variation is the most important systems-level result. Higher output was not obtained by accepting wider product dispersion; instead, the process moved toward a narrower operating window while defects also decreased. For a small food business, this combination is more consequential than nominal speed alone because it increases the proportion of capacity that can be converted into consistent, saleable product.

Hygiene performance and human-machine complementarity

The intervention substantially reduced direct product handling. Hand-contact points during a 600-unit batch decreased from approximately 14 to 5, a 64.3% reduction. The machine performed the filling, forming, folding, and transfer functions that previously required repeated hand contact. The food-contact surfaces were predominantly SUS 304 stainless steel and the principal components were removable for cleaning.

Process-hygiene indicators improved after introduction of the machine and associated operating procedures. Sanitation-SOP compliance increased from 62.0% to 94.0%, PPE compliance from 65.0% to 95.0%, and the equipment-cleanliness score from 68.0% to 96.0%. Sanitation-record completeness increased from 25.0% to 93.0%, while compliance with the project's GMP/HACCP-oriented checks increased from 40.0% to 92.0%. Hygiene nonconformities decreased from 10 to 3 findings, a 70.0% reduction. Twenty-nine of 30 scheduled cleaning activities were completed, corresponding to 96.7% completion.

These findings represent improved process control rather than direct evidence of microbiological risk reduction. No microbial counts were reported before or after implementation. Accordingly, the data support the conclusion that Gyozenova reduced manual contact and strengthened sanitation discipline, but they do not establish a quantified reduction in microbial contamination.

Human capability developed concurrently with machine stabilization. Mean training score increased from 56.8 before training to 88.0 after training. Individual changes were 58 to 90, 55 to 86, 52 to 84, and 62 to 92. The mean paired improvement was 31.25 points. An exploratory paired t test produced $t = 65.3$ with three degrees of freedom ($p < 0.001$); however, the participant number was only four, so the result principally reflects the highly consistent within-person improvements rather than population-level precision. All four participants exceeded the defined competency threshold of 80 after training.

Operational learning was also reflected in preparation time, which decreased from 18 to 11 min over repeated use. The three operators were subsequently able to run the machine at 450 units h⁻¹ without direct supervision. In a set of 12 minor-fault scenarios, participants correctly resolved an average of 11, corresponding to 91.7% success.

Technology acceptance was high after 20 production days. The mean overall score was 4.57 of 5, equivalent to 91.3%. Productivity benefit received the highest reported percentage score (96.0%), followed by product-consistency benefit (95.0%) and fit with production needs (94.0%). Maintainability received the lowest score (85.0%), although it remained within the project's "very high" category. Intention to continue using the system was 93.0%, highlighting both perceived value and the need for ongoing access to maintenance information and technical support.

Labor productivity doubled even though the machine did not remove human involvement from production. The reduction from four directly engaged workers to three operators reflected a

redistribution of work rather than workforce elimination. One employee who had previously performed repetitive folding could contribute to ingredient preparation, packaging, recording, or order processing. This distinction matters when considering automation in small enterprises, where multifunctional labor is often valuable and outright labor displacement may be neither necessary nor desirable.

The results support a model of human-machine complementarity. The machine took over repetitive operations requiring consistent timing and force, while humans retained responsibility for ingredient condition, parameter selection, inspection, sanitation, troubleshooting, and production decisions. Training improved mean competency from 56.8 to 88.0 points, and preparation time decreased from 18 to 11 min. The first five pilot batches also showed a progressive reduction in nonconformity. These findings indicate that technical performance depended partly on operator learning.

This observation aligns with the implementation barriers described for SMEs by Alsaadi (2024) and with the workforce emphasis in the project literature. An automation project can fail if users receive equipment without sufficient process knowledge or ownership. In contrast, the Gyozenova implementation involved operator feedback during design, phased speed increases, practical training, and development of troubleshooting and maintenance procedures. The resulting 91.3% technology-acceptance score suggests that the system was perceived as useful and compatible with the production environment, although maintainability remained the lowest-rated dimension.

Maintainability is therefore a key issue for future scaling. A food microenterprise can handle routine cleaning, inspection, tightening, and minor troubleshooting after training, but specialized gearbox, electrical, or forming-die repair may still require external support. For appropriate automation to be sustainable, spare-part availability, documentation, technician access, and preventive-maintenance discipline should be considered part of the technology package rather than after-sales details.

The hygiene results were substantial at the process level. Direct hand-contact points decreased by 64.3%, hygiene nonconformities by 70.0%, and sanitation-SOP compliance rose to 94.0%. Record completeness and GMP/HACCP-oriented checks also improved markedly. The use of SUS 304 food-contact surfaces and removable components facilitated more structured cleaning.

These changes address an important constraint in manual dumpling production. Repeated hand contact creates multiple opportunities for cross-contact and makes hygiene dependent on worker behavior. Food-safety literature cited in the source report emphasizes the importance of structured food-safety management in small enterprises and the difficulty of implementing such systems consistently (Chernova et al., 2020; Lee et al., 2023). By reducing the number of handling steps and making sanitation a documented operating requirement, the intervention created a stronger procedural basis for hygienic production. More advanced food-safety management can further benefit from structured data and real-time monitoring (Donaghy et al., 2021; Lim et al., 2023).

Nevertheless, the interpretation must remain bounded by the available data. The study did not measure microbial load on products, hands, or equipment surfaces. A reduction in handling and improved sanitation compliance are plausible risk-reduction mechanisms, but they do not prove a specific reduction in *Staphylococcus aureus*, coliforms, total plate count, or other microbiological indicators. Future studies should pair process-hygiene indicators with swab and product microbiology to determine whether procedural improvement translates into measurable biological risk reduction.

The distinction between “hygiene compliance” and “food safety outcome” is also important for publication quality. Overstating safety claims would weaken the scientific argument. The current evidence is strong enough to conclude that Gyozenova improved hygienic process organization, reduced direct handling, and strengthened sanitation traceability. Demonstrating improved microbiological safety requires additional testing.

Digital monitoring, operational economics, and staged smart manufacturing

The production dashboard provided 20 days of post-implementation operational data. Total output was 54,000 units, equivalent to an average of 2,700 units day⁻¹. Of these, 53,136 were recorded as conforming and 864 as defective, matching an overall conformance rate of 98.4% and defect rate of 1.6%. Scheduled operation totaled 120 h, whereas effective operation was 117.6 h. Downtime was therefore 2.4 h or 2.0% of scheduled time, averaging 7.2 min day⁻¹.

Downtime was mainly associated with rapid die cleaning, wrapper-position adjustment, material replenishment, and correction of filling flow. After these causes became visible in the dashboard, operators prepared backup materials and performed pre-production die inspection. Maintenance

completion was 14 of 15 scheduled activities (93.3%), while 58 of 60 sanitation activities were completed (96.7%). Production-record completeness increased from 35.0% at baseline to 94.0%, and inventory-record accuracy increased from 72.0% to 95.0%.

Operational accounting estimates indicated that unit production cost decreased from IDR 2,650 to IDR 2,250, a reduction of 15.1%. Direct labor allocated to the forming process decreased from IDR 480,000 to IDR 360,000 day⁻¹, although the displaced worker was reassigned to other enterprise functions rather than removed from employment. At a stated selling price of IDR 4,000 per unit, gross profit per unit increased from IDR 1,350 to IDR 1,750 and the corresponding reported gross margin increased from 33.8% to 43.8%.

The source project also estimated potential daily revenue of IDR 7.2 million before and IDR 10.8 million after implementation based on production output and the stated unit selling price. These values should be interpreted as capacity-based revenue scenarios rather than independently verified sales receipts. More defensible operational evidence of market responsiveness is the increase in order fulfilment from 78.0% to 96.0%, which indicates that added production capacity was accompanied by improved ability to satisfy recorded demand.

Table 2. Integrated Before-After Performance of the Gyozenova Intervention

Indicator	Before	After	Change	Interpretation
Production capacity	300 units h ⁻¹	450 units h ⁻¹	+50.0%	Stable routine output
Batch time (600 units)	120 min	80 min	-33.3%	Shorter production cycle
Manual handling	108 min/batch	54 min/batch	-50.0%	Lower direct manual workload
Labor productivity	75 units worker ⁻¹ h ⁻¹	150 units worker ⁻¹ h ⁻¹	+100.0%	Higher output per direct worker
Process waiting time	22 min/batch	7 min/batch	-68.2%	Reduced bottleneck accumulation
Weight mean ± SD	22.6 ± 2.22 g	22.5 ± 0.83 g	Mean maintained	Lower dispersion
Weight coefficient of variation	9.8%	3.7%	-62.2%	Improved portion consistency
Overall product conformance	93.3%	98.4%	+5.1 pp	More saleable output
Defect rate	6.7%	1.6%	-76.1%	Lower process loss
Direct hand contacts	14/batch	5/batch	-64.3%	Lower manual contact
Hygiene nonconformities	10 findings	3 findings	-70.0%	Improved process hygiene
Sanitation-SOP compliance	62.0%	94.0%	+32.0 pp	Improved discipline
Operator competency	56.8 points	88.0 points	+55.1%	Higher operational capability
Record completeness	35.0%	94.0%	+59.0 pp	Greater data visibility

Indicator	Before	After	Change	Interpretation
Order fulfilment	78.0%	96.0%	+18.0 pp	Improved responsiveness
Unit production cost	IDR 2,650	IDR 2,250	−15.1%	Operational accounting estimate
Gross margin	33.8%	43.8%	+10.0 pp	At stated IDR 4,000 selling price

Note: pp, percentage points. Inferential tests were exploratory because the field design was single-site and several variables were available only as summary data.

A second layer of transformation occurred through digital monitoring. Prior to implementation, production records were incomplete and did not systematically capture defects, downtime, sanitation, maintenance, or corrective action. After implementation, record completeness reached 94%, and the dashboard provided a daily view of output, conformance, downtime, material use, order fulfilment, and inventory.

This transition is significant because automation without measurement can reproduce inefficiency at higher speed. The dashboard allowed abnormal defect rates, downtime sources, and maintenance needs to become visible. Over 20 production days, the system recorded 54,000 units, 98.4% conformance, and 2.0% downtime. These data can support preventive rather than reactive management, because the owner can connect production outcomes to operating conditions and corrective actions.

The literature cited in the project report similarly positions digital technologies as tools for traceability, quality management, and decision support in food operations (Donaghy et al., 2021; Lim et al., 2023; Peres et al., 2025). The novelty of the current case is not technological sophistication; the dashboard was deliberately simple. Its value lies in appropriateness. A spreadsheet-based system that is actually used may be more effective for a microenterprise than a sensor-rich architecture that exceeds available skills and maintenance resources.

This suggests a staged pathway for smart manufacturing in small food enterprises. Stage 1 is physical process stabilization through appropriate automation. Stage 2 is standardization through SOPs and explicit operating limits. Stage 3 is digital visibility through structured data capture. Stage 4 can then add sensors, automatic counters, weight measurement, machine-state logging, or machine vision where the operational value justifies additional complexity. Food-quality detection research suggests that camera-assisted inspection can become a useful extension when the process and data infrastructure are mature enough to support it (Wu et al., 2023).

The staged approach is also relevant to maintenance and sustainability. Food-processing case evidence links big-data analytics and business-intelligence dashboards with resource optimization and green innovation (Hassani et al., 2025). Cost-conscious Industry 4.0 retrofitting has been explored through non-intrusive IoT and edge/cloud analytics for motor monitoring and predictive maintenance in a food-processing SME (Kotsilitis et al., 2020a). More advanced modular digital-twin strategies have recently been proposed specifically for SME maintenance; scenario-based analyses across agri-food cases reported substantial potential reductions in downtime-related cost and repair time, although these benefits depend on operating assumptions (Nasirinejad et al., 2026). Industry 4.0 tools have also been examined as a means of shortening development processes in an SME supplying tailored food-processing technologies (Urban et al., 2020). These studies reinforce the logic of adding capability incrementally: affordable monitoring and robust maintenance should precede complex analytics, particularly because food SMEs often lack the financial flexibility required for advanced intelligent processing (Raut et al., 2022).

The operational changes were accompanied by improved accounting indicators. Reported unit production cost decreased by 15.1%, while gross profit per unit increased by 29.6% at the stated selling price. Material efficiency rose to 98.0%, and order fulfilment increased to 96.0%. The combination of more saleable product, less waste, and higher capacity provides a plausible mechanism for improved enterprise economics.

However, the economic results should be interpreted conservatively. The daily revenue values in the source report are output-based estimates assuming sale of all produced units at the average stated price. They do not account for demand variability, depreciation, financing cost, taxes, maintenance over a longer horizon, or possible changes in packaging and distribution cost. Similarly, the reported reduction in direct production labor reflects reassignment of one worker rather than necessarily a reduction in total payroll. A full techno-economic analysis should therefore calculate total cost of ownership, machine depreciation, maintenance, energy, financing, utilization rate, product mix, and realized sales over a longer period.

Even with these limitations, several indicators have direct managerial relevance. Lower defect generation reduces ingredient loss; reduced batch time creates capacity for additional orders; higher standardization supports consistent packaging and portioning; and more complete data improve production planning. These factors strengthen the enterprise's readiness for broader distribution channels, where consistency and fulfilment reliability are typically more important than in low-volume informal sales.

Contribution, limitations, and future research

The principal contribution of this study is the demonstration of a multidimensional automation pathway in a real food microenterprise. Gyozenova should not be understood merely as a dumpling-forming machine. The empirical pattern is better described as: automation enabled process integration; process integration reduced manual dependence and waiting; parameter control reduced product variability; standardization and training stabilized operation; and digital monitoring improved visibility of performance. The resulting gains appeared simultaneously in throughput, labor productivity, defect reduction, hygiene compliance, operator competence, and managerial data availability.

This model may be relevant to other labor-intensive foods involving repetitive filling and forming, but generalization should be cautious. The study involved one enterprise, one primary product, and a relatively short post-implementation period. There was no randomized control site. Some baseline and post-intervention measures used different sample sizes, and multiple components of the intervention were introduced together. Consequently, the design cannot isolate the independent causal contribution of the machine, SOPs, training, layout change, or dashboard.

A second limitation is the structure of the available dataset. Individual product-level measurements were not available for all variables, so several statistical analyses relied on reported summary values. Exploratory inferential tests therefore depend on assumptions that could not be fully verified. Future work should retain time-stamped unit-level product weights, batch identifiers, machine settings, environmental variables, defect categories, and downtime events to allow mixed-effects modeling and statistical process-control analysis.

Third, microbiological outcomes were not measured. Future validation should include surface swabs and product microbiology before and after automation. Fourth, ergonomic outcomes were inferred from reduced manual handling but not quantified using posture, repetition, fatigue, or musculoskeletal assessment. Fifth, the economic analysis should be expanded to total cost of ownership and realized cash flow over at least 6-12 months.

Beyond shop-floor control, the next development stage could connect production data with traceability and enterprise-level technology upgrading. A blockchain framework for decentralized supply chains combines provenance, smart-contract logic, identifiers, and IoT monitoring, but explicitly notes that SME adoption depends on institutional accountability, legal alignment, and inclusive design (Abaker, 2025). At the enterprise-policy level, impact assessment of a technology-upgrading program for MSMEs found technology, process, and innovation assimilation to be the most heavily weighted performance criterion in its analytic hierarchy model (Rivera et al., 2020). Evidence from food-sector SMEs also suggests that frugal digital technologies can support innovation performance and streamline information exchange, although the appropriate mix depends on local capability and business context (Mashoko, 2025). For Gyozenova, these studies point to a logical future trajectory rather than a claim about the current system: first preserve the demonstrated process stability, then strengthen automated data capture and maintenance, and only thereafter connect quality, inventory, traceability, and market information. This sequencing protects the central advantage of appropriate automation—operational usefulness under resource constraints—while creating a pathway toward higher digital maturity.

Future research should therefore test Gyozenova or similar systems across multiple small food enterprises, product formulations, and operator groups. A stepped-wedge or matched-site design could strengthen causal inference while remaining practical for community-based technology deployment. Sensorized weight, automatic production counting, and camera-based defect recognition could provide richer continuous data. Most importantly, future studies should examine whether the performance gains observed here persist over time and whether operators can maintain process capability without intensive external support.

Accordingly, the numerical changes should be interpreted as field-implementation evidence rather than isolated causal effects of a single hardware component. The strongest inference supported by the design is that the integrated intervention was associated with a coherent pattern of operational improvement across throughput, variability, defects, hygiene-process compliance, operator capability, and data completeness. Replication with contemporaneous controls and unit-level longitudinal data is required before the magnitude of each component effect can be generalized beyond this production setting.

CONCLUSION

The implementation of Gyozenova transformed a manual, worker-dependent gyoza-forming process into a more integrated, parameter-controlled, and data-visible production system. Under the stable operating condition of 450 units h⁻¹, throughput increased by 50%, production time for a 600-unit batch decreased by 33.3%, manual handling time decreased by 50%, and labor productivity doubled. These efficiency gains were accompanied by improved product stability rather than a quality trade-off. Mean product mass remained close to the 22.5-g target, while the coefficient of variation decreased from 9.8% to 3.7% and the defect rate declined from 6.7% to 1.6%.

The intervention also improved the organization of hygiene and production management. Direct hand-contact points decreased by 64.3%, hygiene nonconformities by 70.0%, sanitation-SOP compliance reached 94.0%, and operator competency increased from 56.8 to 88.0 points. The digital dashboard provided a 20-day operational record of 54,000 units with 98.4% conformance and 2.0% downtime. Technology acceptance reached 91.3%, indicating that the system was compatible with the operational context, although maintainability and access to technical support remain important for long-term use.

Taken together, the findings support a broader proposition for small-scale food manufacturing: useful automation is not simply the substitution of manual labor with machinery. Its value arises when mechanical integration is combined with standardized process parameters, operator capability, sanitation discipline, maintenance, and production data. Gyozenova therefore provides a field-based proof of concept for “appropriate smart automation” in a food microenterprise. The results are promising but should be validated through longer monitoring, multi-site replication, unit-level process data, microbiological testing, ergonomic assessment, and full life-cycle economic analysis.

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