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INTEGRATED QUALITY CONTROL 4.0 MODEL FOR READY MEALS AND CANNED MEAT PRODUCTION

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Abstract:
The objective of this study was to develop an integrated Quality Control 4.0 model for ready meals and canned meat production. The research was conducted as an industrial case study based on a 2024 supplier quality dataset, an inventory of control devices used in the production system, and a structured literature review on Food Quality 4.0 and ready-meal safety. The dataset included an aggregated total of 3,939 deliveries, 209 non-conforming raw materials and 209 complaints. Visible supplier-level records included 58 coded suppliers, 3,572 deliveries and 188 non-conforming raw materials. Descriptive statistics, Pareto analysis, supplier non-conformity rates and technology-function mapping were used. The results showed that the overall non-conformity rate in the aggregated dataset was 5.31%. The dominant defect descriptors were appearance non-conformity (110 cases), fat within the +2% tolerance zone (41 cases), exceeded fat content (38 cases), and odour/colour non-conformity (31 cases). Supplier risk was concentrated: the five suppliers with the highest number of non-conforming materials accounted for 59.0% of visible supplier-level non-conformities. The proposed model integrates raw material inspection, composition standardisation, thermal-process validation, hygiene control, packaging inspection and KPI-based decision support. The model provides a practical framework for moving from reactive quality control towards data-driven quality assurance and improvement in meat-based convenience food manufacturing.

Key words: canned meat products, Food Quality 4.0, quality control, ready meals; supplier risk

INTRODUCTION

Ready meals and canned meat products are positioned at the intersection of convenience, safety and industrial repeatability. Their production involves raw material sourcing, preparation of meat and vegetable components, filling, packaging, thermal processing, storage and distribution. Each of these stages may influence sensory quality, nutritional value, product stability and consumer safety. Recent research on ready-to-eat meals indicates that safety and quality control should cover the entire supply chain, from raw material sourcing to consumption, with particular attention to detection methods, sterilisation technologies, packaging innovations and storage conditions [1]. This is particularly important in meat-based ready meals and canned products, where raw material variability, microbiological risk, formulation repeatability and thermal process validation jointly determine the reliability of the final product.

The operational specificity of food processing requires improvement methods that are sensitive to process variability, perishability and short decision cycles. Recent research in food processing has shown that Lean Manufacturing can be strengthened by simulation-based approaches combining Gemba walks, check sheets, Pareto analysis, Fishbone diagrams, Value Stream Mapping and Monte Carlo simulation [2]. Such a perspective is relevant to ready meals and canned meat production because raw-material non-conformities, delays in preparation stages, cleaning operations, filling accuracy, packaging defects and thermal processing conditions may influence both process stability and product quality. Therefore, quality management in this sector should not be limited to final product inspection but should include structured analysis of variability, bottlenecks and risk sources throughout the production flow. This perspective is also consistent with research on agile management in Polish food processing enterprises, where flexibility, rapid response to market requirements, resource reconfiguration and responsibility for product quality are treated as important organisational capabilities supporting competitiveness and adaptation to changing consumer expectations [3].

The increasing complexity of food production has also changed the role of quality management. Food Quality 4.0 is understood as the integration of food science, quality assurance and Industry 4.0 tools, including sensors, Internet of Things (IoT), big data, artificial intelligence (AI), machine learning and digital traceability [4]. In this approach, quality is no longer limited to final inspection. It becomes a data-driven system that supports real-time monitoring, process optimisation, decision-making and continuous improvement across the value chain. This direction is consistent with current Industry 4.0 research, in which digital transformation, smart manufacturing, machine learning and the Internet of Things are among the key concepts shaping the development of production systems [5, 6]. These concepts provide a theoretical basis for developing data-driven quality control models in food manufacturing. This technological basis should also be interpreted in a broader socio-economic context. Industry 4.0 is associated not only with the implementation of digital technologies, but also with socio-economic evolution driven by automation, efficiency improvement and productivity growth. Therefore, Quality Control 4.0 in food manufacturing can be viewed as part of a wider transformation of production systems, work organisation and managerial decision-making [7].

At the same time, the implementation of Industry 4.0 solutions in enterprises remains challenging. Recent studies indicate that companies may expect benefits such as increased production efficiency, logistics optimisation and product quality improvement, but they also face barriers related to implementation costs, employee skills, cybersecurity and data integration [8]. These findings are important for the present study because an integrated Quality Control 4.0 model should be designed as an evolutionary and practically feasible solution based on available control infrastructure, rather than as an abstract fully digitalised system. Consequently, the proposed model deliberately starts from available supplier records and existing inspection devices, because earlier studies on SMEs have shown that the practical implementation of Industry 4.0 requires incremental solutions adjusted to financial, organisational and competence-related constraints [9].This is particularly relevant for food producers, where existing inspection devices, laboratory measurements and supplier records often constitute the first layer of digital quality management.

In food manufacturing, the Food Quality Management 4.0 (FQM 4.0) framework links digital technologies with five managerial quality functions: quality design, quality control, quality improvement, quality assurance, and quality policy and strategy [10]. However, published studies still focus mainly on quality control and quality assurance, while practical applications connecting supplier data, process measurements and management decisions remain limited. This gap is relevant for ready meals and canned meat production, where raw meat variability, thermal safety, packaging integrity, hygiene status and formulation conformity must be controlled simultaneously. Research on the implementation of modern information technologies in manufacturing enterprises also highlights the need to combine strategic system design with local, process-level data acquisition and improvement activities [11].

A further challenge concerns the difference between the declared adoption of advanced technologies and their mature operational integration. Recent research on enterprise AI implementation indicates that technology adoption alone does not guarantee organisational readiness, data maturity or effective decision support [12]. This argument is important for Quality Control 4.0 in food production because AI-based decision support should be treated as a future development layer built on reliable data collection, harmonised indicators and clearly defined quality decision rules. A similar logic is visible in prescriptive maintenance research, where effective decision-making requires the integration of diagnostic data, production schedules, resource availability and organisational constraints into a unified framework [13]. In the context of ready meals and canned meat products, this reasoning can be extended to quality control: inspection data should be linked with supplier performance, production batches, control devices and managerial decisions.

Traceability is another key component of Quality Control 4.0. Recent research has proposed architectures combining RFID, databases, backend automation and blockchain-based records to improve supply chain traceability [14]. Although such solutions may be developed in different agri-food contexts, the logic of linking physical product identification with digital traceability records is transferable to meat-based ready meals and canned products. In such systems, supplier codes, raw material lots, production batches, thermal process records and packaging inspection results could be connected in a traceability architecture supporting transparency, accountability and faster response to non-conformities.

The aim of this study was to develop an integrated Quality Control 4.0 model for ready meals and canned meat production based on industrial data and available control infrastructure. The following research questions were formulated:

- RQ1: What types of raw-material non-conformities dominate in the case dataset?
- RQ2: Which suppliers generate the highest quality risk?
- RQ3: How can control devices and quality data be integrated into a Quality Control 4.0 model for ready meals and canned meat products?

LITERATURE REVIEW

Industrial production of prepared dishes increasingly depends on standardisation, mechanisation and continuous production. Research on central kitchen engineering and ready-to-cook foods emphasises strict control of raw materials, cooking, sterilisation, packaging and logistics to reduce safety risks and preserve sensory quality [15, 16]. These studies indicate that prepared dishes should be treated as complex production systems in which food technology, production engineering, packaging and distribution management interact with quality and safety outcomes.

In meat-based convenience foods, safety and quality depend on technological and organisational factors. Ready meals may be affected by contamination, inadequate thermal treatment or microbial growth during storage [17]. Process interventions combined with packaging can improve microbial and sensory quality [18], while processing and safety control of ready-to-eat meals require validated sterilisation and packaging solutions that protect consumers without unnecessary sensory or nutritional losses [1]. Therefore, quality control in ready meals and canned meat production must consider raw material condition, formulation stability, heat-treatment effectiveness and packaging reliability as mutually connected factors.

From a management perspective, supplier quality management is critical because raw material variability enters the production system before internal process control begins. Supply chain quality management aims to coordinate activities and stakeholders in order to monitor, analyse and improve products, processes and services [19]. In meat-based ready meals, supplier quality indicators should therefore be connected with production quality indicators, such as fat content, protein, salt, pH, water activity, foreign-body detection, package integrity and hygiene results. This connection is essential because non-conforming raw material may influence recipe repeatability, thermal processing behaviour, labelling accuracy and final product acceptance.

Quality 4.0 expands traditional quality control by introducing digital data collection and decision support. The FQM 4.0 framework indicates that sensors support all managerial quality functions, especially quality control and quality improvement. AI and machine learning are primarily associated with faster and more accurate quality evaluations, big data supports process improvement, and IoT or blockchain can improve traceability and strategic decision-making [10]. Digitalised automated analysis has also been described as a key direction in Food Quality 4.0, where non-destructive fingerprinting techniques, smart sensors, AI and big data may increase the speed, objectivity and reliability of quality assessment [20]. This study builds on these frameworks by translating them into a practical model for meat-based ready meals and canned meat production.

The meat industry has its own digital transformation context. The concept of Meat 4.0 refers to the application of Industry 4.0 technologies in the meat supply chain, including robotics, IoT, big data, augmented reality, cybersecurity and blockchain [21]. Current analyses of meat processing also emphasise automation, smart technologies, waste minimisation, energy efficiency and sustainability as important directions for future industrial development [22]. In ready meals and canned meat production, these directions are relevant because the same production system must simultaneously control raw meat variability, composition, hygiene, thermal safety and packaging quality.

Recent techno-managerial analysis of Industry 4.0 technologies in food quality and safety systems shows that AI is mainly used for product quality control, while IoT supports process quality control; data analysis is the most frequently addressed element of the quality control circle, whereas corrective and proactive actions remain less developed [23]. This confirms the need for models that do not stop at data acquisition but connect measurements with decision rules and improvement activities. More general Quality 4.0 research also stresses that digital quality management should align technological capabilities with quality management practices in order to improve cost, time, efficiency and product quality [24].

This integrated approach allows for a holistic understanding of quality parameters, from raw material to finished product, thereby enhancing predictive capabilities for potential deviations and enabling proactive corrective measures. The paradigm shift from reactive inspection to proactive, data-driven quality assurance is particularly important in complex food manufacturing environments, where product integrity and consumer safety depend on the combined performance of suppliers, operators, control devices, hygienic procedures and thermal processing systems [10, 20, 23, 24]. The subsequent sections of this study present the methodology for integrating these elements into a cohesive Quality Control 4.0 model based on industrial data and the available control infrastructure.

METHODOLOGY OF RESEARCH

The research was designed as a single industrial case study. The analysed company was a Polish producer of ready meals and canned meat products. To protect commercial information, suppliers are identified only by numerical codes. The empirical material consisted of two internal data sources: a 2024 supplier delivery and non-conformity worksheet, and a list of control devices with their measurement scope [25, 26].

The supplier worksheet contained an aggregated total row and 58 visible supplier-level records. The total row reported 3,939 deliveries, 209 non-conforming raw materials and 209 complaints. The visible supplier records summed to 3,572 deliveries, 188 non-conforming raw materials and 188 complaints. This difference was retained transparently in the analysis: the total row was used for overall company-level indicators, while supplier-level rankings were calculated only from visible coded supplier records.

Six categories of defect descriptors were available: exceeded fat content, odour/colour non-conformity, appearance non-conformity, fat within the +2% tolerance zone, protein within the -2% tolerance zone, and non-conforming temperature. Since the sum of defect descriptors exceeded the number of complaints, descriptors were treated as attribute occurrences rather than strictly mutually exclusive complaint classes.

The following indicators were calculated: overall non-conformity rate (NCR), supplier non-conformity rate, and supplier contribution to visible non-conformities. NCR was calculated as the number of non-conforming raw materials divided by the number of deliveries and multiplied by 100%. Supplier contribution was calculated as the number of non-conforming raw materials from a supplier divided by

the sum of visible supplier-level non-conformities. Pareto logic was used to identify the highest-risk suppliers and dominant defect descriptors.
The second methodological step was technology-function mapping. Each control device was assigned to one or more Quality 4.0 functions: quality control, quality assurance, quality improvement, quality design, and quality policy and strategy. The mapping was used to develop an integrated model that connects raw material inspection, process validation, packaging control and managerial decision support.

RESULTS OF RESEARCH
The aggregated data (Table 1) show that 209 non-conforming raw materials were recorded in 3,939 deliveries, which corresponds to an overall non-conformity rate of 5.31%.

Table 1
Empirical dataset used in the case study

Indicator	Aggregated total row	Visible supplier-level rows
Number of suppliers	not applicable	58 coded suppliers
Deliveries	3,939	3,572
Non-conforming raw materials	209	188
Complaints	209	188
Non-conformity rate	5.31%	5.26%
Main analytical use	overall quality indicator	supplier ranking and risk assessment

The same number of complaints was registered, which indicates that each non-conforming raw material was reflected in a complaint record at the aggregated level. The visible supplier-level records produced a similar rate: 188 non-conforming materials in 3,572 deliveries, or 5.26%. The dominant defect descriptor was appearance non-conformity, with 110 occurrences. It represented 49.3% of all descriptor occurrences. The second most frequent descriptor was fat within the +2% tolerance zone (41 occurrences, 18.4%), followed by exceeded fat content (38 occurrences, 17.0%) and odour/colour non-conformity (31 occurrences, 13.9%). Protein within the -2% tolerance zone and non-conforming temperature were marginal descriptors. This structure (Table 2) suggests that quality risk in the case system is driven mainly by visual/sensory attributes and fat-related composition variability.

Table 2
Structure of defect descriptors in the 2024 dataset

Defect descriptor	Occurrences	Share of descriptor occurrences
Appearance non-conformity	110	49.3%
Fat within +2% tolerance zone	41	18.4%
Exceeded fat content	38	17.0%
Odour/colour non-conformity	31	13.9%
Non-conforming temperature	2	0.9%
Protein within -2% tolerance zone	1	0.4%

Supplier-level results show a clear concentration of risk (Table 3). Supplier 32 generated 60 visible non-conforming raw materials, which is 31.9% of all visible supplier-level non-conformities. Supplier 58 generated 17 cases, supplier 56 generated 14 cases, supplier 52 generated 11 cases, and supplier 49 generated 9 cases. Together, the five suppliers with the highest number of visible non-conformities generated 111 cases, equal to 59.0% of visible supplier-level non-conformities.

Table 3
Suppliers with the highest number of visible non-conforming raw materials

Supplier code	Deliveries	Non-conforming materials	NCR	Contribution to visible non-conformities	Risk interpretation
32	1,079	60	5.56%	31.9%	strategic high-volume supplier
58	202	17	8.42%	9.0%	high contribution and elevated rate
56	466	14	3.00%	7.4%	high volume with moderate rate
52	55	11	20.00%	5.9%	low-medium volume with high rate
49	99	9	9.09%	4.8%	medium risk
42	28	8	28.57%	4.3%	low volume with very high rate
40	129	8	6.20%	4.3%	medium volume risk
55	179	8	4.47%	4.3%	medium volume risk

The risk profile changes when volume is considered. Supplier 32 had the largest number of non-conformities, but its non-conformity rate was 5.56% because it also had the highest number of deliveries. Suppliers with lower delivery volumes, such as supplier 52 (20.0%), supplier 42 (28.57%), supplier 43 (36.36%) and supplier 36 (45.45%), had much higher non-conformity rates. This indicates that supplier risk assessment should combine absolute number of defects, relative defect rate and delivery volume rather than rely on a single indicator.
The control infrastructure (Table 4) available in the case company covers key stages of meat-based ready meal and canned product production.

Table 4
Mapping of control devices to Quality Control 4.0 functions

Model layer	Data/control source	Measured or controlled attributes	Main quality function
Supplier and raw material control	Supplier dataset, Meat Master II, FoodScan 2	supplier history, fat, mass, foreign bodies, protein, water, colour	QC, QA, QI
Composition and batch standardisation	FoodScan 2, potentiometric titrator	fat, protein, salt, sodium, pH, acidity, water activity	QC, QI, QD
Thermal process and hygiene control	Ellab TrackSense Pro, ATP luminometer	temperature, pressure, RLU hygiene results	QA, QC
Packaging and final inspection	X-Ray Analysis, Oxybaby	contaminants, mass, package integrity, components, O_2/CO_2	QC, QA
Digital decision layer	KPI dashboard, Pareto, supplier risk matrix	NCR, trends, risk classes, corrective actions	QI, QPS

Meat Master II supports raw meat scanning, fat measurement, mass control and detection of foreign bodies such as metal and bones. FoodScan 2 supports composition analysis of homogenised meat products, including fat, water, protein, collagen, salt, sodium, water activity, ash and colour. X-Ray Analysis supports final product inspection by detecting contaminants, measuring mass, assessing package integrity, identifying damaged products and counting components. Oxybaby enables O_2 and O_2/CO_2 control in modified atmosphere packages. Ellab TrackSense Pro supports thermal-process validation through temperature and pressure monitoring. The luminometer supports hygiene verification using ATP results expressed in RLU, and the potentiometric titrator supports salt, pH and acidity testing [26].

INTEGRATED QUALITY CONTROL 4.0 MODEL

The proposed model (Fig. 1) consists of five integrated layers. Layer 1 is supplier and raw material control. It uses supplier history, NCR, complaints, Meat Master II results and FoodScan 2 measurements to classify incoming material and determine inspection intensity.

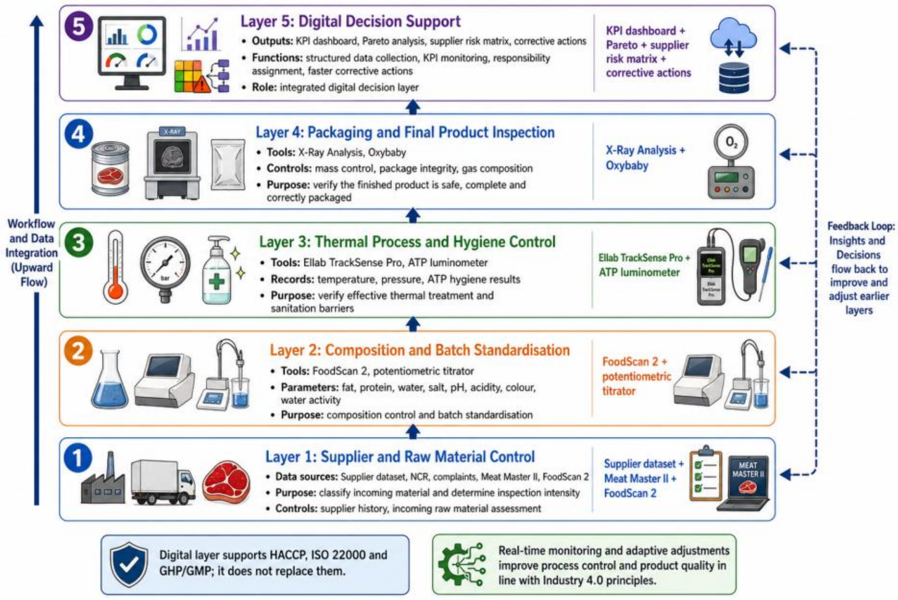

Fig. 1 Proposed Integrated Quality Control 4.0 model for ready meals and canned meat production

Alt text: *Five-layer Quality Control 4.0 model linking supplier control, batch standardisation, safety, packaging inspection and KPI support.*

Long description: *The diagram presents a five-layer integrated Quality Control 4.0 model for ready meals and canned meat production. Layer 1 covers supplier and raw material control using supplier history, NCR, complaints, Meat Master II and FoodScan 2. Layer 2 concerns composition and batch standardisation using FoodScan 2 and titration to monitor fat, protein, water, salt, pH, acidity, colour and water activity. Layer 3 covers thermal process and hygiene control based on Ellab TrackSense Pro and ATP luminometry. Layer 4 includes packaging and final product inspection using X-Ray Analysis, Oxybaby, mass control and package integrity checks. Layer 5 is the digital decision-support layer, integrating KPI dashboards, Pareto analysis, supplier risk matrices and corrective actions. Feedback loops connect all layers and support continuous improvement.*

Layer 2 is composition and batch standardisation. It uses FoodScan 2 and titrator results to control fat, protein, water, salt, pH, acidity, colour and water activity. Layer 3 is process safety control. It uses Ellab temperature and pressure records and ATP hygiene results to verify that thermal treatment and sanitation barriers are effective. Layer 4 is packaging and final product inspection. It uses X-Ray Analysis, Oxybaby and mass/package integrity controls to verify that the finished product is safe, complete and correctly packaged. Layer 5 is the digital decision layer. It integrates data into KPI dashboards, supplier risk matrices and corrective action workflows. Therefore, the proposed Quality Control 4.0 model should be interpreted not as a replacement for HACCP, ISO 22000 or GHP/GMP, but as a digital layer that supports their execution through structured data collection, KPI monitoring, responsibility assignment and faster corrective actions [27]. This interpretation is consistent with the broader quality management system approach, in which ISO 9001-based implementation supports process formalisation, responsibility assignment, corrective actions and continuous improvement, while expected benefits include improved organisational control and quality performance [28].This holistic framework facilitates real-time monitoring and adaptive adjustments, significantly enhancing overall process control and product quality throughout the manufacturing lifecycle [29]. This integration aligns with Industry 4.0 principles, leveraging advanced sensor technologies and intelligent data analysis to detect extraneous inclusions, monitor temperatures, and optimize raw material processing, thereby proactively addressing potential quality deviations [30, 31].

The model is consistent with Quality 4.0 because it transforms isolated inspections into an integrated data architecture. Raw material data, process data, hygiene data and final inspection data can be linked by batch number, supplier code, product code, production date and line. In its basic form, the model supports descriptive and diagnostic analytics. After integration with real-time device outputs, it can support predictive analytics, for example by identifying combinations of supplier, raw material parameters and process deviations that increase the probability of final rejection or complaint. This shift from reactive to proactive quality management, underpinned by real-time data acquisition and analysis, is a hallmark of Quality 4.0, emphasizing adaptive and automated solutions for enhanced quality planning and control [32]. From a managerial perspective, the model assigns each quality function a clear role. Quality control detects deviations in raw materials, process parameters and finished products. Quality assurance verifies that process barriers, especially thermal validation and hygiene, are stable and documented. Quality improvement uses Pareto analysis, supplier ranking and trend dashboards to reduce recurring non-conformities. Quality design uses historical measurement data to refine specifications and tolerance limits. Quality policy and strategy use supplier risk classes and investment priorities to develop a long-term roadmap for digital quality management. This integrated approach transforms traditional quality management into a dynamic, data-driven system, aligning with the broader principles of Industry 4.0 by leveraging interconnectivity and real-time insights to optimize production outcomes and foster continuous improvement [33, 34]. Furthermore, the integration of real-time monitoring and predictive analytics enables proactive identification of potential risks, allowing for timely corrective actions before deviations escalate [35]. The proposed key performance indicators for the digital decision layer are summarised in Table 5.

Table 5

Proposed key performance indicators for the digital decision layer

KPI	Formula or data source	Management use
Overall NCR	non-conforming raw materials/deliveries x 100%	monitor stability of incoming quality
Supplier NCR	supplier non-conformities/supplier deliveries x 100%	rank and qualify suppliers
Supplier contribution	supplier non-conformities/all visible non-conformities x 100%	identify Pareto suppliers
Composition deviation rate	number of fat/protein/salt deviations/tested batches x 100%	control formulation and labelling risk
Thermal validation compliance	valid thermal records/validated thermal records x 100%	verify safety barrier
Packaging non-conformity rate	rejected packages/inspected packages x 100%	control final product integrity
Hygiene compliance	ATP results below limit/ATP tests x 100%	verify sanitation effectiveness

DISCUSSION

The results confirm the practical relevance of integrating supplier quality data with process and device-level control. The case dataset shows that almost half of all defect descriptors were related to appearance. This is important because appearance is both a supplier quality issue and a product acceptance issue. In ready meals and canned meat products, raw material appearance may influence consumer perception, formulation stability and process yield. Although the present study focuses on industrial quality control rather than tourism services, recent research on mass catering confirms that the consistency and reliability of meal quality are important determinants of customer satisfaction; therefore, sensory and appearance-related deviations should be treated as customer-relevant quality signals, not only as internal non-conformities [36]. Therefore, the model should not treat visual defects as subjective observations only, but as measurable quality events that trigger supplier feedback and corrective actions.

Fat-related descriptors formed the second major risk area, with 79 occurrences. This supports the inclusion of Meat Master II and FoodScan 2 in the first two model layers. Rapid incoming inspection and batch standardisation can support early acceptance, segregation, reclassification, intensified sampling or formulation adjustment.

The supplier results also show why Quality 4.0 should combine quality engineering and management systems. A supplier with many deliveries may generate the largest absolute number of defects, while small suppliers may have the highest relative defect rate. A dashboard based on both indicators would enable differentiated responses: strategic development for high-volume suppliers, intensified qualification for high-rate suppliers, and reduced inspection for stable low-risk suppliers. This supports the transition from reactive complaint handling to risk-based quality assurance.

The proposed model contributes to FQM 4.0 by providing a sector-specific application for meat-based convenience foods. It responds to the need for real-world applications in specific food sectors by connecting supplier data and control devices with managerial quality functions [10]. This framework facilitates enhanced transparency and traceability across the production lifecycle, integrating seamlessly with existing enterprise resource planning systems to provide a holistic view of quality performance [37]. This approach also leverages the principles of Industry 4.0, integrating advanced machine learning techniques for predictive quality control and process optimization [38].

However, the current maturity of the model is limited by data availability. The analysed dataset is aggregated at supplier level and does not contain batch identifiers, product codes, production lines, measurement timestamps, device outputs or final consumer complaint outcomes. Therefore, the model should be interpreted as a structured design and preliminary empirical diagnosis rather than a fully validated digital twin or AI-based prediction system. To validate effectiveness, future work should integrate device outputs with batch-level production and complaint data over a longer period.

CONCLUSIONS

The study developed an integrated Quality Control 4.0 model for ready meals and canned meat production. The case dataset showed an aggregated raw-material non-conformity rate of 5.31% and a visible supplier-level rate of 5.26%. The main defect descriptors were appearance non-conformity, fat-related deviations and odour/colour non-conformity. Supplier risk was concentrated, as five suppliers generated 59.0% of visible supplier-level non-conformities.

In response to RQ1, the case dataset indicates that raw-material non-conformities were dominated by appearance non-conformity (110 occurrences; 49.3% of descriptor occurrences), followed by fat-related deviations: fat within the +2% tolerance zone (41 occurrences; 18.4%) and exceeded fat content (38 occurrences; 17.0%). Odour/colour non-conformity was the next important category (31 occurrences; 13.9%). Thus, the main incoming-quality problem was not an isolated technological parameter, but a combination of visual/sensory deviations and composition-related deviations that may affect product acceptance, recipe repeatability and labelling reliability.

In response to RQ2, the highest supplier quality risk was concentrated in a small group of suppliers. In absolute terms, supplier 32 was the key risk source, generating 60 non-conforming raw materials and 31.9% of all visible supplier-level non-conformities. Suppliers 58, 56, 52 and 49 followed, and together with supplier 32 they accounted for 59.0% of visible supplier-level non-conformities. However, a risk-based interpretation should also consider relative non-conformity rates; therefore, supplier 42 (NCR

28.57%) and supplier 52 (NCR 20.00%) require intensified qualification, sampling or corrective actions despite lower delivery volumes.

In response to RQ3, control devices and quality data can be integrated into a Quality Control 4.0 model by connecting supplier history, incoming raw-material inspection, composition standardisation, thermal-process validation, hygiene verification, packaging inspection and KPI-based decision support. In this model, Meat Master II, FoodScan 2, X-Ray Analysis, Oxybaby, Ellab TrackSense Pro, ATP luminometry and titration do not function as isolated measurement tools, but as linked data sources supporting supplier risk classification, trend monitoring, corrective-action workflows and continuous improvement in ready meals and canned meat production.

The proposed model integrates supplier quality assessment, raw material inspection, batch standardisation, process safety validation, hygiene verification, packaging inspection and KPI-based decision support. It demonstrates how existing industrial control devices can be used not only for isolated measurements, but also as data sources for Quality 4.0 management functions. The model may support supplier risk management, HACCP documentation, process improvement and strategic investment in digital quality infrastructure. In the longer term, such a roadmap may also provide a basis for extending Quality Control 4.0 toward Quality 5.0, where digital technologies are combined with human-centricity, resilience, sustainability and next-generation operational excellence [39].

The main limitation is the absence of batch-level and device-output data. Future research should connect measurements from Meat Master II, FoodScan 2, X-Ray Analysis, Ellab, Oxybaby, ATP luminometry and titration with production batches, product families and final quality outcomes. This would allow statistical validation of the model and development of predictive algorithms for early detection of quality risk in meat-based ready meals and canned meat products.

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