Digital Transformation and AI-Powered Unmanned Instant Noodle Production Systems

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Abstract

This conceptual review explores how Industry 4.0 and Artificial Intelligence (AI) technologies can be integrated into instant noodle production to enhance efficiency, sustainability, and quality control. Although, in recent years, instant noodle sector has grown into a major global market, conventional production systems remain highly dependent on manual labor, energy-intensive operations, and rigid process control, which makes it difficult to ensure consistent quality and low environmental impact. Methodologically, the present study adopts a conceptual review and framework-development design based on a structured literature review and theme-oriented synthesis of recent Industry 4.0 and AI applications in food manufacturing. Building on this synthesis, we propose a four-layer conceptual framework that combines sensing and data acquisition, AI and analytics, automation and robotics, and cyber–physical integration to support AI-powered, potentially unmanned instant noodle production lines. The results illustrate how technologies such as the Internet of Things (IoT), smart sensors, machine vision, robotics and Big Data analytics can be orchestrated along the noodle process (mixing, steaming, frying or drying and packaging) to improve operational performance and enable "dark factory" concepts. In parallel, we discuss key challenges for small and medium-sized enterprises (SMEs), including high initial investment costs, data security concerns and limited digital competence. The study concludes with an outline of a future research agenda that prioritizes cost-effective modular and cloud-based solutions for SMEs, training and local support mechanisms to facilitate technology adoption, and AI-driven Big Data analytics to predict consumer preferences and demand trends. In conclusion, the study provides a sector-specific conceptual roadmap for the digital transformation of instant noodle production within the broader context of Industry 4.0 and AI-driven food manufacturing.

Keywords: Industry 4.0, Artificial Intelligence, Sustainability, Noodle Production, Robotic Automation.

Review Article / *Received: 29 July 2025, Accepted: 12 December 2025, Published Online: 19 December 2025.*

1. Introduction

The food industry has historically evolved in parallel with technological progress, continuously adapting to changing consumer expectations and global production demands (Duke-Rohner, 2007). With the emergence of Industry 4.0, this evolution has been accelerated by the integration of cyber–physical systems, the Internet of Things (IoT), smart sensors, robotics, cloud computing and artificial intelligence (AI), enabling data-driven production environments that prioritize efficiency, traceability, and sustainability (Hassoun et al., 2022). Among food manufacturing sectors, owing to its multi-stage, high-volume and labor-intensive processes (Upadhyay et al., 2022), instant noodle production stands out as a strong candidate for digital transformation.

Globally, the instant noodle industry has become a major economic segment within the packaged food sector, with annual consumption reaching 120.21 billion servings in 2023 (World Instant Noodles Association, 2023). Recent market analyses indicate that this segment constitutes a multi-billion US dollar market, which inderline sits strategic contribution to the global processed food economy (Fortune Business Insights, 2023). While Asia-Pacific region accounts for almost 86% of global demand, consumption continues to rapidly expand in Europe and North America (Fortune Business Insights, 2023). Despite this growing market and economic significance, the industry faces persistent structural challenges—including high energy consumption, significant labor dependency, rising operational costs, waste management issues, along with increasing pressure to meet sustainability targets (Tjandra et al., 2016). These

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https://doi.org/10.56479/ijgr-60

challenges are further amplified by the need to maintain consistent quality and ensure supply continuity in the face of increasing global demand, highlighting the urgency of transitioning towards more flexible, automated and environmentally responsible production systems.

By enabling real-time process monitoring, predictive control, energy optimization, and autonomous decision-making, Industry 4.0 technologies offer transformative solutions to these challenges (Zhong et al., 2017). IoT-based sensors can collect continuous data on dough rheology, moisture, frying or drying performance and line speed, while robotics and automated handling systems minimize human error and improve throughput. Predictive maintenance algorithms reduce unplanned downtime by identifying equipment failures before they occur (Iqbal et al., 2017). In addition, energy monitoring platforms and digital twins can optimize resource use, thus reducing carbon emissions and operational waste (Herrmann & Thiede, 2009). Collectively, these innovations contribute to more agile, cost-effective and sustainable manufacturing practices (Milczarski et al., 2021).

AI provides an additional layer of capability, enabling intelligent interpretation of large-scale production data. AI-based image processing systems can evaluate noodle structure, color, and uniformity in real time to ensure consistent quality (Mokhtar et al., 2011). Machine-learning models support process optimization by dynamically adjusting parameters such as moisture, temperature and cooking conditions to improve energy efficiency and product performance (Bandyopadhyay et al., 2021). Furthermore, Big Data analytics allows manufacturers to better understand consumer preferences, forecast demand, and develop personalized product formulations (Horvat et al., 2019). As a result, AI-enabled systems have the potential to revolutionize both operational and strategic decision making in the instant noodle industry.

However, although Industry 4.0 and AI technologies have been widely applied in dairy, bakery, beverage and other food sectors to improve quality, speed and sustainability (Konur et al., 2023; Iqbal et al., 2017), a significant gap remains in noodle-specific research. Previous studies tended to focus on incremental improvements within traditional production systems and did not offer an integrated conceptual framework for fully automated or "dark factory" instant noodle production. To date, no comprehensive model has been proposed that would map Industry 4.0 and AI technologies across all stages of noodle manufacturing—from dough mixing to packaging—while simultaneously addressing the unique operational, economic, and sustainability challenges of this sector.

In this context, the present study seeks to fill this gap by developing a conceptual framework for the integration of Industry 4.0 and AI technologies into instant noodle production systems. Designed as a conceptual review and framework-development study, it synthesizes current literature across food manufacturing, digital transformation, and automation to propose a structured, four-layer blueprint for AI-powered and potentially unmanned production environments. Major contributions of the present review include (i) formulating an integrated model specifically tailored to the noodle industry; (ii) identifying digital transformation strategies that enhance energy efficiency, quality control, and operational sustainability; and (iii) outlining actionable pathways for small and medium-sized enterprises (SMEs) through modular and cost-effective technologies.

The remainder of this study is structured as follows: Section 2 explains the methodological approach based on a structured literature review and thematic synthesis. Section 3 presents and discusses the proposed conceptual framework in relation to existing applications in food manufacturing. In Section 4, we combine the conclusion with future research directions, emphasizing technological, economic, and sustainability insights relevant to the next generation of instant noodle production systems.

2. Methodology

This study adopts a conceptual review and framework-development design. Rather than generating new empirical data, we synthesize existing literature on digital transformation in food manufacturing and translates these insights into a domain-specific conceptual model for AI-powered, potentially unmanned instant noodle production lines. Conceptual articles of this type are widely used to organize fragmented knowledge, clarify emerging technological phenomena, and propose integrative models or frameworks that can guide future empirical research and industrial implementation (Gilson & Goldberg, 2015; Jaakkola, 2020). Therefore, the focus of the present study is on building a theoretically grounded and practically relevant blueprint, rather than on testing hypotheses with primary data.

The review is based on a structured literature search conducted between January and November 2024 in major academic databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink and Google Scholar. To capture the intersection of digital transformation and food manufacturing, we used combinations of keywords related to Industry 4.0, AI and food systems, such as "Industry 4.0" AND "food industry" / "food manufacturing" / "food processing"; "artificial intelligence" OR "machine learning" AND "food" / "food quality" / "food safety"; "IoT" OR "smart sensors" AND "food production"; "robotics" AND "food processing" / "packaging"; and "instant noodles" OR "noodle production". We retained peer-reviewed journal articles, conference papers and reputable institutional reports that addressed Industry 4.0, AI, IoT, robotics, smart sensors or digital transformation in food or analogous process industries, as well as studies on instant noodles, pasta and cereal-based products relevant to process design, energy use or quality control. Publications from 2015 onwards were prioritised to reflect the acceleration of Industry 4.0 and AI applications in manufacturing and the food sector (Lee et al., 2014; Zhong et al., 2017), while seminal earlier works on cyber–physical systems and smart factories were retained when conceptually important. Non-scientific sources, studies dealing exclusively with primary production (e.g., agriculture) rather than food processing, and papers that did not report applications or conceptual models relevant to food manufacturing were excluded. After the screening of titles, abstracts and full texts of the candidate papers, a core set of studies was identified and complemented through backward and forward snowballing from key references.

Building on this synthesis, we propose a four-layer conceptual framework for AI-powered instant noodle production systems. The first layer, sensing and data acquisition, comprises IoT sensors, machine vision and spectroscopic tools (e.g., NIR, FTIR) to monitor critical quality and process parameters in real time. The second layer, AI and analytics, includes machine-learning models for quality prediction, anomaly detection, energy management, and predictive maintenance. The third layer, automation and robotics, covers programmable logic controllers, robotic handling, autonomous steaming, frying, drying, and packaging units that can execute control decisions with minimal human intervention. The fourth layer, cyber–physical integration, links these elements through real-time data platforms, digital twins and remote supervision capabilities consistent with "dark factory" or unmanned operation concepts. In remainder of this paper, this framework is instantiated step by step along the instant noodle production process and discussed in relation to existing Industry 4.0 and AI applications in the food sector.

As a conceptual review and framework-development study, this research does not present new empirical data or quantitative validation of the proposed model. This is a deliberate methodological choice, consistent with the aim of defining and structuring a future research and implementation agenda, rather than evaluating a specific pilot plant or case study. Consequently, the framework should be viewed as a theoretically informed and practice-oriented proposition that requires further testing through industrial case studies, simulation and digital-twin experiments, as well as cost–benefit and adoption analyses in different organizational contexts, particularly small and medium-sized enterprises. These limitations are acknowledged in order to invite future work that will refine, extend, and empirically validate the concepts outlined in the present review.

3. Results and Discussion

3.1. Industry 4.0 and Technological Transformation in Food Production

The integration of Industry 4.0 technologies into food production processes not only enhances efficiency and reduces operational costs, but also offers significant benefits in terms of environmental sustainability (Cagnetti et al., 2021). These technologies improve energy efficiency along production lines and contribute to the reduction of carbon footprints (Beier et al., 2020). In continuous high-throughput systems such as instant noodle plants, where dough mixing, steaming, frying, drying, and packaging are performed in tightly coupled stages, the combined energy demand of multiple thermal units and conveyor systems makes resource optimization particularly critical (Tjandra et al., 2016; Obadi et al., 2022; Guner et al., 2024). In this context, the adoption of Industry 4.0 technologies can help to address long-standing challenges related to energy consumption, process control and waste generation.

In particular, IoT-based sensors and robotic systems can monitor process and energy variables in real time, thus eliminating unnecessary usage and promoting energy conservation (Ghag et al., 2024). Continuous monitoring of production processes helps to identify energy-intensive stages, allowing for targeted optimization (Cagnetti et al., 2021). In the case of instant noodles, critical operations such as steaming, frying, and hot-air drying are known to dominate the overall energy balance of the line; therefore, in order to balance product quality with energy use, real-time data on temperature, residence time and moisture loss are essential (Tjandra et al., 2016; Meenu et al., 2021). Predictive maintenance systems can also detect equipment failures in advance—such as burner malfunctions in fryers or airflow instabilities in dryers—thereby minimizing production downtime and associated energy losses (Zonta et al., 2020). In this regard, the automation and optimization solutions enabled by Industry 4.0 support environmental sustainability while reducing both carbon emissions and waste generation (Beier et al., 2020). The adoption of such technologies in the food industry has already accelerated the shift towards more eco-friendly production systems (Ghag et al., 2024), and similar principles can be translated to instant noodle manufacturing.

To date, the successful implementation of Industry 4.0 technologies in food manufacturing has yielded remarkable outcomes, particularly in the dairy, bakery and beverage sectors (Khoroshailo et al., 2020; Yadav et al., 2022). In these industries, IoT-based systems enable continuous monitoring of product quality, while robotic systems significantly enhance production speed and hygiene (Amin & Rahman, 2018). Analogous needs exist in instant noodle production, where dough mixing, sheeting, and cutting are still frequently performed with substantial manual intervention, leading to variability in dough rheology, sheet thickness, and strand geometry (Upadhyay et al., 2022; Obadi et al., 2022). IoT sensors and closed-loop controllers can stabilize these upstream operations by monitoring flour quality, dough moisture, and mixing torque, while robotic handling systems can standardize cutting and portioning, thereby improving both throughput and dimensional accuracy.

In the bakery sector, robotic systems have been deployed to improve efficiency in dough shaping, baking, and packaging operations (Logeswaran et al., 2022). Comparable robotic technologies can be used in instant noodle lines to automate tasks such as block shaping, colander loading, in-line inspection, and final packaging (Pitjamit et al., 2024). Robots can assist in handling hot noodle blocks leaving the fryer or dryer, reducing direct operator contact with high-temperature equipment, minimizing occupational risk, and improving product consistency. In addition, image-processing algorithms can be employed for shape consistency and surface defect detection, thereby enhancing both food safety and visual quality (Zhu et al., 2021).

Internet of Things (IoT) technology enables real-time data collection along the entire noodle production line—from flour silos to finished product packaging (Bigliardi et al., 2022; Jagtap et al., 2021). These data are used to continuously monitor every stage of the process and to facilitate optimization. In instant noodle manufacturing, parameters such as dough temperature and moisture during mixing, sheet thickness during rolling, internal temperature and water activity during steaming and frying, and final moisture and oil content during drying can be continuously monitored (Tjandra et al., 2016; Meenu et al., 2021). Such systems not only optimize processing parameters, but also ensure consistent food quality and safety (Bouzembrak et al., 2019). Furthermore, by detecting unnecessary energy consumption and reducing the carbon footprint of production lines, IoT sensors contribute to energy efficiency (Ömerali & Kaya, 2023). Every stage of the line can be digitally tracked, enabling real-time process control, traceability, and continuous improvement (Wang et al., 2024).

Traditional instant noodle production lines tend to be largely dependent on manual labor, particularly in areas such as line supervision, quality inspection, secondary packaging, and in-plant logistics. This reliance inherently limits production speed, increases error rates, and results in high energy consumption due to suboptimal set-points and unplanned stops (Jagtap et al., 2021; Obadi et al., 2022). By contrast, Industry 4.0-based systems significantly enhance manufacturing efficiency (Logeswaran et al., 2022). IoT sensors enable real-time process optimization, while robotic systems and AI applications increase production speed and ensure continuous quality monitoring (Anwar et al., 2023). As a result, production costs can be reduced while both throughput and energy efficiency are significantly improved (Sharifi Nia et al., 2024). While, in conventional systems, quality control is typically conducted manually, which can be inconsistent and error-prone, Industry 4.0 technologies automate many of these tasks, reducing defects and improving overall quality assurance (Jimeno-Morenilla et al., 2021).

In summary, the integration of Industry 4.0 technologies into instant noodle production offers far more efficient, rapid, safe and environmentally friendly solutions as compared to those afforded by traditional manufacturing systems. IoT and robotic systems streamline production and enhance sustainability, while AI-based quality control systems ensure greater accuracy and consistency across critical stages such as dough mixing, cooking, and packaging. Therefore, this digital transformation provides the technological foundation on which the subsequent sections of this paper build a noodle-specific conceptual framework for AI-enabled, potentially unmanned production lines.

3.2. AI Applications and Their Impact on Food Production

In recent years, AI has emerged as one of the most transformative technologies in food manufacturing, enabling real-time optimization, enhanced quality control, improved operational efficiency, and more accurate forecasting of consumer demand (Zatsu et al., 2024). In instant noodle production—a sector characterized by high throughput, multi-stage processing, and strict quality requirements—AI applications offer substantial benefits, particularly in dough mixing, steaming, frying, cutting, drying, and packaging operations. By integrating machine learning, computer vision, and predictive analytics, AI-savvy manufacturers can address several long-standing challenges associated with manual inspection, process variability, and equipment instability (Yu et al., 2025).

AI-driven quality control systems have become increasingly common in global food production facilities. For instance, Nestlé and Ajinomoto have incorporated AI-based computer vision technologies on packaging and forming lines to detect defects such as under-fried blocks, color deviations, and breakage—a common issue in instant noodle production. These systems identify micro-defects that frequently remain undetectable to human inspectors, thereby significantly reducing product rework, sensory deviations, and customer complaints (De Vries et al., 2023). In instant noodle lines, AI-based image processing can continuously monitor noodle block uniformity, thickness, moisture distribution, and surface color. This ensures consistency in frying and drying stages, which are critical for texture and shelf stability. By reducing defect rates, AI directly lowers raw material waste and improves the overall production yield.

Another critical AI application that provides substantial cost savings and operational reliability is predictive maintenance. Global manufacturers such as PepsiCo have deployed AI-enabled predictive maintenance to monitor vibration, torque, load, and thermal profiles in high-speed food processing equipment, reporting up to a 20% reduction in unplanned downtime (Misra et al., 2022). Similar systems can be adapted to instant noodle production where dough mixers, cutting machines, steamers, fryers, and continuous dryers are prone to wear-induced failures. AI continuously analyzes equipment behavior to forecast malfunctions before they occur, allowing manufacturers to schedule maintenance proactively. This reduces emergency stoppages, prevents product loss due to incomplete batches, and extends equipment lifespan. From an economic standpoint, predictive maintenance decreases maintenance costs, minimizes downtime-related losses, and ensures uninterrupted production flow—all of which are key factors for high-volume manufacturers such as Nissin and Indofood.

AI also plays an increasingly important role in optimizing process parameters at critical stages of noodle production. Machine-learning models can identify optimal settings for dough hydration, mixing time, steaming temperature, frying duration, and drying airflow based on real-time sensor data (Jin et al., 2020). For instance, improper moisture control during steaming or over-frying can lead to breakage during packaging or poor rehydration properties. In these settings, AI-powered process control systems make continuous micro-adjustments, reducing variability between batches, which leads to improved texture, reduced oil uptake, lower energy use, and enhanced product stability across long-term storage. Internal case studies conducted at the Research and Development Center of Erişler Gıda A.Ş. revealed that AI-based process optimization decreased energy consumption by 8–12% during drying and frying, indicating measurable environmental and economic benefits.

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Furthermore, in the domain of consumer analytics, AI enables manufacturers to better understand evolving market expectations and rapidly tailor new product designs (Zamani et al., 2023). By integrating sales data, social media sentiment analysis, and flavor trend mapping, AI systems can forecast demand for specific product types, such as low-sodium noodles, air-dried alternatives, plant-based formulations, or regionally adapted flavor profiles. Companies like Nongshim and Maruchan have started experimenting with AI-enhanced R&D to adjust seasoning formulations based on predicted consumer preferences (Mavani et al., 2022). For instant noodle producers, this translates into more targeted new product development, reduced risk of unsuccessful launches, and improved competitiveness in global markets.

AI also significantly contributes to sustainability and resource efficiency. Through energy monitoring and optimization algorithms, AI systems detect unnecessary heating cycles in fryers, excess airflow in drying tunnels, or prolonged idle times in conveyors (Keleko et al., 2022). By identifying these inefficiencies, AI reduces energy costs and supports carbon emission reduction targets. In addition, AI-driven robotic systems reduce material waste by improving cutting precision and increasing packaging accuracy, while integrated tracking systems ensure full traceability from raw material intake to final product distribution (Agrawal et al., 2023).

In summary, by improving product quality, reducing operational costs, enhancing process stability, and enabling data-driven decision-making, AI applications in instant noodle production offer substantial and measurable benefits. Previous real-world examples of using AI—from Nestlé's AI-based defect detection to PepsiCo's predictive maintenance and Nissin's process optimization—demonstrate the transformative potential of AI for the noodle sector. As the global industry faces increasing pressure for efficiency, sustainability, and responsiveness to consumer demands, AI-powered manufacturing solutions provide an essential framework for future competitiveness and innovation.

3.3. Integration of Industry 4.0 and AI in Instant Noodle Production

The integration of Industry 4.0 technologies into the instant noodle production process plays a critical role in achieving goals related to efficiency, quality, and sustainability (Kakani et al., 2020). Through the use of IoT-based sensors, robotic systems, and AI algorithms, raw material waste can be minimized and energy efficiency can be achieved (Meenu et al., 2021). These technologies support sustainability targets by enhancing energy efficiency throughout the production process (Zhao et al., 2025). Along with other Industry 4.0 components, the new technologies ensure quality at every stage by optimizing the production flow and minimizing environmental impact (Kakani et al., 2020).

Dough mixing and formulation represent the most critical initial step in instant noodle production, as this stage directly affects the quality of subsequent processing steps (Guner & Basdogan, 2025). During formulation, each ingredient is dosed according to its specific properties, and this dosing process is precisely controlled using IoT-based sensors (Dadhaneeya et al., 2023). Key parameters such as moisture content, temperature, and additive concentrations are continuously monitored and analyzed (Liberty et al., 2024). Then, the data collected from IoT sensors are further examined using near-infrared (NIR) spectroscopy and Fourier-transform infrared (FTIR) spectroscopy technologies (Bouzembrak et al., 2019). NIR determines the proportions of key ingredients—such as water and flour—by measuring the absorption or reflection of light at specific wavelengths, enabling rapid and accurate compositional analysis (Grassi & Alamprese, 2018). This facilitates homogeneous dough mixing and allows for real-time identification of inconsistencies, thereby improving both quality and process efficiency (Ziani et al., 2025). On the other hand, FTIR analyzes the interaction between infrared light and the material to evaluate the molecular composition of key compounds, such as proteins and starches. This technology is crucial for ensuring ingredient compatibility and validating formulation uniformity on the molecular level (Saji et al., 2024).

AI algorithms process the large volume of data generated by IoT sensors to dynamically optimize the dough mixing and formulation stages (Jossa-Bastidas et al., 2023). For instance, using machine-learning techniques, moisture imbalances can be detected and corrected in real time, with automatic adjustments suggested—such as adding water or flour—when necessary. Collectively, these technologies reduce both energy consumption and raw material waste in noodle production while maintaining high product quality. Furthermore, homogeneous blends and precise dosing contribute to the optimization of noodle texture, taste, and cooking performance (Ikram et al., 2024).

Critical stages in the instant noodle production process are shaping, steaming, and frying. During the shaping stage, robotic systems form the noodles into desired shapes and sizes, increasing production speed and ensuring dimensional accuracy (Görgülü, 2025). AI-powered image processing technologies enable real-time analysis of quality parameters such as noodle shape, size, and surface uniformity, thus allowing defective products to be rapidly identified and removed from the line (Vithu & Moses, 2016).

In the subsequent steaming stage, the internal moisture content and temperature balance of the dough are closely monitored (Chen & Yu, 2022). IoT-based sensors measure the internal temperature, moisture levels, and water loss of the noodles in real time (Liberty et al., 2024). These data are then used to optimize the cooking time, which directly impacts texture and flavor of the noodles. AI-supported systems also maintain optimal steam temperature and duration to ensure uniform cooking (Wu & Sun, 2013). In addition, real-time color analysis technologies help to determine the doneness level of noodles, thereby contributing to the identification of ideal cooking parameters (Kang & Sabarez, 2009). This ensures that quality criteria are consistently met in the subsequent frying or drying stages.

During frying, parameters such as free fatty acid (FFA) content and peroxide value of the oil are continuously monitored via IoT sensors and analyzed using AI algorithms (Gu et al., 2022). These analyses allow for timely oil replenishment to maintain quality standards. Industry 4.0 components provide real-time data across all of these processes, thus significantly enhancing quality control, production efficiency, and waste reduction (Bhat et al., 2025).

Further critical stages that directly impact product quality and efficiency in instant noodle production are drying and packaging. In the drying phase, the final moisture content, fat levels, and doneness of the noodles are analyzed in detail using near-infrared (NIR) spectroscopy and advanced imaging systems (Bouzembrak et al., 2019). NIR technology measures the absorption and reflection of light at specific wavelengths to accurately determine moisture and fat contents in the noodles (Li et al., 2020). This ensures homogeneous and standard-compliant drying throughout the process. In addition, high-resolution imaging systems continuously evaluate noodle surface smoothness and doneness in real time (Wu & Sun, 2013). The data obtained from these technologies are analyzed by AI algorithms, enabling dynamic optimization of drying temperature, airflow, and duration (Ramirez-Asis et al., 2022). As a result, product quality is sustainably maintained, while production efficiency is enhanced and waste is minimized (Pandey & Mishra, 2024).

At the packaging stage, robotic systems and AI-powered image processing technologies conduct a final inspection of quality parameters such as shape, size, and color, automatically removing any defective products from the line (Liaw & See, 2024). Moreover, X-ray technology is used to verify package weight and content, as well as to detect foreign matter (Adams et al., 2021). Integrated with IoT-based systems, these solutions optimize the production process, minimize human error, ensure consistent product quality, and enhance customer satisfaction (Bhatia & Ahanger, 2021).

The storage and distribution stages constitute the final yet critical phases of production. Through the integration of Industry 4.0 and AI technologies, these processes are optimized to enhance both food safety and the efficiency of logistics operations (Zatsu et al., 2024). Inventory management systems such as First-In, First-Out (FIFO) and Last-In, First-Out (LIFO) ensure accurate and efficient stock handling (Alamri & Syntetos, 2018). The FIFO system allows products to be dispatched based on their production date, which is particularly crucial in the food industry to maintain freshness and safety (Murphy et al., 2024). By contrast, the LIFO system is more suitable for products with longer shelf lives (Alamri & Syntetos, 2018).

In both FIFO and LIFO systems, traceability of products is enhanced using IoT-based sensors and AI algorithms (Maheshwari et al., 2021). From a food safety perspective, traceability is achieved through IoT sensors and cloud-based data platforms during storage operations. Each product is identified using QR codes or RFID tags, and this information is stored in real time in a centralized database. This enables tracking of every movement—from production to dispatch—thus allowing for rapid response in the event of a product recall (Bhat et al., 2025).

AI-powered warehouse management systems optimize inventory levels and plan shipping routes based on consumer demand. In addition, these systems monitor energy consumption, preventing unnecessary expenditures and contributing to the reduction of carbon emissions (Huang et al., 2022). Solutions integrated with Industry 4.0 components enhance both quality and efficiency throughout all stages of the entire supply chain—from production to consumption.

4. Conclusion and Future Research

The integration of Industry 4.0 and AI technologies into instant noodle production presents transformative opportunities for the global food industry. Collectively, IoT-based monitoring, robotic automation, image-processing systems, AI-assisted quality control, near-infrared (NIR) spectroscopy and modular automation architectures can make noodle production faster, more consistent, and more resource-efficient. Along with supporting improvements in energy efficiency, reductions in carbon footprint and enhanced product quality, these technologies also enable more flexible and responsive production systems. In the long term, AI-driven sensing and control mechanisms provide the technological foundations for highly automated, and potentially unmanned, instant noodle manufacturing environments.

Concurrently, several critical challenges must be addressed to realize these benefits at scale. High upfront investment costs for hardware, software, integration and maintenance remain a major barrier, particularly for small and medium-sized enterprises (SMEs). The adoption of interconnected AI and IoT systems is further complicated by concerns about data security and privacy, as well as exposure to cyber threats. In addition, many SMEs face a shortage of technical expertise in automation, data analytics and AI model management, which can slow or distort digital transformation efforts. Without deliberate strategies to tackle these cost, security and skills constraints, the diffusion of Industry 4.0 and AI technologies in instant noodle production will remain uneven and fragmented.

In response to these challenges, based on the results of the present review, we outline several practical directions that future research and industrial practice should prioritize. First, it is essential to develop cost-effective, modular and cloud-based technological solutions tailored to SMEs. Modular robotic units that can be added incrementally to existing lines—starting, for example, with packaging or palletizing and later extending to dough handling, steaming, frying and drying—would allow small producers to invest step by step, rather than commit to fully integrated systems from the outset. Furthermore, cloud-based AI platforms and software-as-a-service (SaaS) models can reduce the need for on-site servers and specialized IT infrastructure, making advanced analytics, predictive maintenance and quality-prediction tools accessible through subscription or pay-per-use schemes. Such architectures can significantly lower entry barriers while still delivering tangible gains in efficiency and quality.

Second, it is essential that training programs and local support mechanisms for SMEs are designed and implemented in a more systematic way. The effective use of AI and Industry 4.0 technologies depends not only on the availability of hardware and software, but also on the capacity of the workforce to interpret data, fine-tune models, and respond to automated insights. Therefore, future research should explore models for regional training centers, digital academies, and demonstration plants specialized in food and noodle manufacturing. These hubs could provide hands-on training, standardized curricula and vendor-neutral guidance on technology selection and implementation. Collaborative schemes between universities, technology providers, and industry associations may further support SMEs through mentoring, technical helpdesks, and on-site coaching during the early phases of adoption. In this context, designing effective capacity-building frameworks is as important as designing the technologies themselves.

Third, energy efficiency and sustainability constitute a key frontier for both research and practice. By continuously monitoring energy use and dynamically adjusting set-points, AI- and IoT-enabled energy management systems can optimize process conditions across the noodle line—from dough mixing and steaming to frying, drying and cooling. Future studies should focus on developing and validating such systems under real production conditions, quantifying their impacts on energy consumption, greenhouse gas emissions and operating costs. Integrating life-cycle assessment (LCA) with AI-based process control could provide powerful tools for guiding low-carbon process design and for benchmarking different technological configurations in instant noodle production.

Finally, there is a clear need for practice-oriented empirical work that would test and refine the conceptual framework proposed in this study. Industrial case studies, pilot implementations, simulation and digital-twin experiments, as well as cost–benefit and risk analyses in different organizational contexts, would be necessary to translate the theoretical blueprint into robust design guidelines for AI-powered noodle factories. Such work should not only evaluate technical performance, but also consider organizational readiness, workforce acceptance, supply-chain implications, and regulatory constraints.

The present review has several limitations that need be acknowledged. First, this article is conceptual in nature and does not report new empirical data or quantitative validation of the proposed framework. Second, the evidence base is limited primarily to peer-reviewed sources published in English from 2015 onwards and indexed in major databases such as Scopus, Web of Science, IEEE Xplore, ScienceDirect and SpringerLink. This focus may have led to the omission of relevant case studies, proprietary industrial reports or non-English publications, particularly from SMEs and emerging economies. Third, the heterogeneity of study designs, technologies, and performance indicators in the reviewed literature prevented a systematic quantitative comparison of costs, energy use or quality outcomes across different solutions. Finally, considering the rapidly evolving nature of Industry 4.0 and AI technologies, some specific tools or platforms mentioned in this article may change or be superseded over time. These limitations should be borne in mind when interpreting the findings and when using the framework to guide investment, policy or strategic decisions.

Notwithstanding the limitations outlined above, the integration of Industry 4.0 and AI technologies into instant noodle production offers substantial potential gains in productivity, product quality, energy efficiency, and environmental sustainability. Yet, realizing this potential—especially for SMEs—requires the development of modular and cloud-based solutions that would reduce initial investment costs, the establishment of targeted training and local support structures, and the design of energy-efficient, AI-enabled process control strategies. By advancing practical solutions in these areas and empirically validating them in industrial settings, future research can help noodle manufacturers to build more competitive, resilient, and sustainable production systems aligned with the emerging paradigm of AI-powered unmanned food manufacturing.

Declaration of Competing Interest

The authors declare that they have no financial or non-financial competing interests.

Author's Contributions

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H. Başdoğan (0000-0001-9332-4618): *Data Collection, Investigation, Research Design, Research Coordination, Methodology.*
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