Journal of Applied Economic Sciences
Volume XXI, Spring, Issue 2(92), 2026

Technological Determinants of Economic Efficiency in the Food Manufacturing Industry: An Applied Analysis

Oleksandr BOZHOK
https://orcid.org/0009-0004-5127-2775
Department of Tourism, Hotel and Restaurant Business
Vinnytsia Institute of Trade and Economics, State University, Ukraine
ohlazunov@gmail.com

Andrian ULINICI
https://orcid.org/0000-0001-8766-7788
Department of Finance and Accounting, Faculty of Economic Sciences
University of European Studies of Moldova, Republica Moldova
ulinici.andrian07@gmail.com

Inna MINIAILENKO
https://orcid.org/0000-0002-0388-6199
Department of Economics, Entrepreneurship and Marketing
Educational and Scientific Institute of Finance, Economics, Management and Law
National University "Yuriy Kondratyuk Poltava Polytechnic, Ukraine
minyaylenko.inna25@gmail.com

Maksym SYNYAVSKYY
https://orcid.org/0009-0003-0773-5798
Department of Staff and Marketing Management, Faculty of Economics
Zaporizhzhia National University, Ukraine
sinyavskiy05@gmail.com

Lilia BUBLYK
https://orcid.org/0009-0008-5886-1440
Department of Organisational Management
Lviv Politechnic National University, Ukraine
Bublyk.lilia2016@gmail.com

Article's History
Received 28th of January, 2025; *Revised* 4th of March, 2025; *Accepted* 19th of March, 2025; *Available online*: 30th of March, 2026. *Published* as article in the Volume XXI, Spring, Issue 2(92), March, 2026.

Suggested Citation
Bozhok, O., Ulinici, A., Miniailenko, I., Synyavskyy, M., & Bublyk, L. (2026). Technological Determinants of Economic Efficiency in the Food Manufacturing Industry: An Applied Analysis. *Journal of Applied Economic Sciences*, Volume XXI, Spring, 2(92), 613 – 633
https://doi.org/10.57017/jaes.v21.2(92).13

Abstract

This paper examines the impact of innovative technologies on the economic efficiency of food manufacturing enterprises under conditions of market volatility and sustainability pressures. Addressing the lack of empirical evidence in existing literature, the research develops an integrated framework combining technological clustering and econometric modelling.

Based on a dataset of 20 technologies (2020–2025), the study estimates β-coefficients for key performance indicators, including return on investment (ROI), cost efficiency, and productivity. The results confirm a strong and statistically significant relationship between technological adoption and economic performance (R^2 = 0.713). Digital technologies, particularly Machine Vision, Big Data analytics, and Smart Packaging, demonstrate the highest aggregated impact.

The findings indicate that optimized technology portfolios can increase ROI by 19–26%, reduce unit costs by up to 18%, and improve labour productivity by approximately 25%. The study contributes a quantitative, multi-criteria framework linking technological innovation with economic efficiency and supporting strategic investment decision-making.

Keywords: economic efficiency; food manufacturing; total factor productivity; technological innovation; industry 4.0; transaction costs.

JEL Classification: D24; L66; O14; O33.

Introduction

In the context of globalization, increasing resource constraints, and tightening environmental regulations, food manufacturing enterprises are under growing pressure to enhance their economic efficiency and operational resilience. The transition toward Industry 4.0, characterized by the integration of artificial intelligence, digital platforms, advanced analytics, and automation, has emerged as a critical pathway for improving productivity, optimizing resource allocation, and strengthening competitive positioning in volatile markets (Şchiopu, 2025; Ghencea & Stanciu, 2025).

Despite the rapid diffusion of innovative technologies across the agri-food sector, the existing literature remains fragmented in terms of quantifying their economic impact. Most studies emphasize technological potential or sustainability dimensions, but lack a systematic econometric validation of how specific technologies influence firm-level performance indicators, such as return on investment (ROI), cost efficiency, and productivity. This gap is particularly relevant in transitional and emerging economies, where investment decisions must be justified through measurable economic outcomes.

Against this background, the present study aims to formalize and empirically assess the impact of innovative technologies on the economic efficiency of food manufacturing enterprises. The research adopts an integrated analytical framework combining functional classification, technological clustering, econometric modelling, and multi-criteria evaluation.

To achieve this aim, the study pursues the following research objectives:

- To systematize and classify innovative technologies in the food manufacturing sector, by identifying their functional roles and the main economic channels through which they influence firm performance. This objective provides the conceptual foundation for structuring the analysis and grouping technologies into relevant clusters.
- To empirically assess the impact of technological innovation on economic efficiency, with a focus on key performance indicators such as return on investment (ROI), cost reduction, and productivity growth. This is achieved through econometric modelling and the estimation of β-coefficients, allowing for the identification of statistically significant relationships.

- To identify optimal technological configurations and support investment decision-making, by comparing aggregated β-effects across technologies and developing a multi-criteria investment framework. This enables the prioritization of innovation strategies based on their overall economic impact.

These objectives are operationalized through the econometric framework presented in Section 2, while the empirical validation is provided in Section 3.

1. Literature Review

The increasing complexity of global food systems, driven by resource constraints, technological disruption, and sustainability imperatives, has intensified academic interest in the role of innovation as a determinant of economic efficiency in the food manufacturing sector. Recent studies emphasize the transformative potential of Industry 4.0 technologies, including artificial intelligence, big data analytics, and cyber-physical systems, in enhancing productivity, optimizing resource allocation, and improving supply chain resilience. However, despite the growing body of literature, existing research remains fragmented, often focusing on specific technologies or sustainability dimensions without providing a unified, empirically grounded framework for assessing their economic impact across multiple performance indicators.

Initially, Fei *et al.* (2025) found that the introduction of innovative technologies in UPA (Urban and Peri-urban Agriculture) increased economic efficiency by reducing transaction costs, intensifying spatial use and increasing agricultural profitability. The authors proposed increasing R&D funding, institutionalizing technology transfer, promoting the economic viability of business models and forming multi-stakeholder innovation clusters.

In this context, da Silva & Sehnem (2025) found that foodtech start-ups actively implemented Industry 4.0 technologies (automation, IoT, biotechnology, Big Data) to increase the economic performance of circular business models and the creation of closed supply chains. The authors recommended institutionalizing multi-actor cooperation, strengthening regulatory support, and stimulating economic viability through long-term innovation depreciation policies.

The role of technological integration is confirmed by the study of Farrukh Shahzad *et al.* (2025), which empirically demonstrated that the implementation of Industry 4.0 technologies indirectly increased the sustainable performance of the food industry through green-oriented collaboration, circular practices and technological readiness. It was found that the moderating effect of environmental dynamics strengthened the integral effect of digital transformation.

In contrast, Kayode & Aladejebi (2025) found that the level of Industry 4.0 technological diffusion in local food production remains fragmented: Big Data analytics ($\beta = 0.347$) and cyber-physical systems ($\beta=0.290$) showed limited variability in their impact on resource logistics ($R^2=0.223$). The integration potential was blocked by the lack of competence capital, institutional infrastructure immaturity, and low adaptability of digital environments.

At the same time, Xie *et al*. (2025) empirically proved that the digital economy significantly increased the resilience of the agri-food system by eliminating the allocation asymmetry of labour and capital resources and increasing adaptive flexibility. The maximum increase in the resilience index ($\beta=0.5312$) was recorded in the central provinces with increased infrastructural and political support.

In parallel, Foumakoye (2025) empirically confirmed that the implementation of artificial intelligence (AI), Internet of Things (IoT) sensors, and machine learning (ML) in the logistics of the organic segment of the local agri-food chain significantly reduced food losses ($R^2=0.78$; $p<0.001$). Predictive analytics, blockchain tracking, and edge infrastructure technologies have enhanced operational resilience, although barriers of high capital intensity, and regulatory fragmentation were also identified.

In view of the foregoing, Senyange *et al.* (2025) proved that tissue engineering technologies are shaping a new paradigm of agri-food systems, providing bioengineered intensification of yield, nutritional density, and ecological resilience, while simultaneously capitalizing on the cultured meat market. The need for regulatory convergence and adaptive regulatory stratification for the institutionalization of TE products in the global food chain is argued.

Continuing the study of agro-technological transformations, Vettriselvan (2025) demonstrated that aeroponics as a high-tech form of soilless farming provided accelerated biomass generation, increased yields, and resource efficiency in controlled agro-environments. Testing in urban and vertical farming systems confirmed its commercial feasibility and ecological minimization.

In this context, Kantal *et al.* (2025) demonstrated that the integration of information technology in aquaculture provided increased productivity, accurate resource allocation, and optimization of logistics chains, increasing operational profitability and sustainability of production. IT tools, in particular water quality analytics, SCM and predictive modelling, contributed to the economic efficiency and ecological sustainability of aqua-systems.

Given the intra-industry differences, Yong Chin *et al.* (2025) found that the technical efficiency of SMEs in food processing is high (CRS=0.940; VRS=0.986), while significantly lower indicators were recorded for LSE (CRS=0.673; VRS=0.942). The results of the study indicate a polarized impact of factors: training and R&D costs for SMEs were the key drivers, while infrastructure and foreign trade were key for LSE.

The analysis of publications confirmed the multifactorial impact of innovations on the economic efficiency of food manufacturers, in particular through the integration of Industry 4.0, IoT, and predictive analytics. Both direct and indirect effects were established, which necessitates the formalization of influence mechanisms taking into account industry specifics, regional asymmetries and the level of institutional maturity.

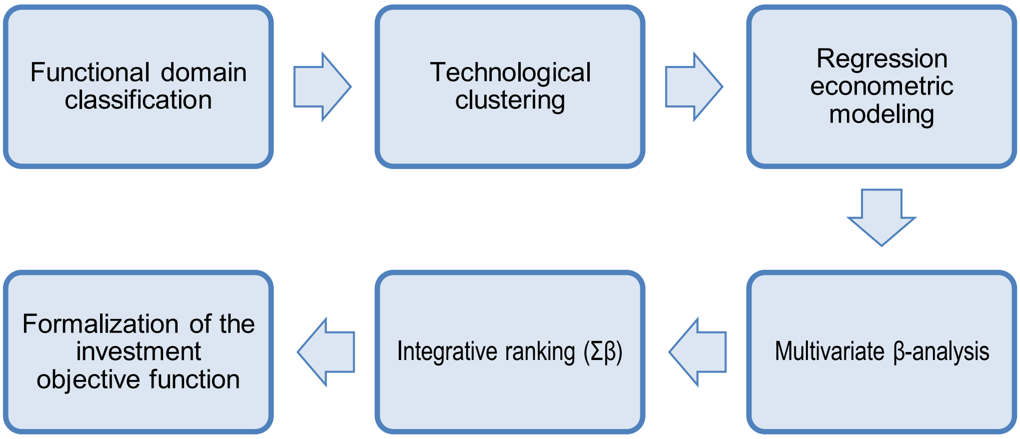
2. Empirical Strategy and Methodology

2.1. Research Design and Analytical Framework

The research follows a structured multi-stage analytical framework aimed at assessing the impact of technological innovation on the economic efficiency of food manufacturing enterprises. The study integrates qualitative classification techniques with quantitative econometric modelling to ensure both conceptual clarity and empirical robustness.

The research design includes: (i) identification and systematization of relevant technological innovations, (ii) functional and technological clustering, (iii) specification of econometric models, and (iv) evaluation of innovation effects using multi-criteria performance indicators. The overall analytical flow is illustrated in Figure 1.

Figure 1: Research Design



Source: Created by the authors

2.2. Econometric Methodology

The study employs a combination of complementary analytical and econometric methods to assess the impact of technological innovations on the economic efficiency of food manufacturing enterprises.

First, a functional domain classification is applied to structure innovations according to their economic, operational, and environmental effects. This step enables the identification of the main channels through which technological adoption influences firm performance.

Second, technological clustering is used to group innovations based on their integration mechanisms within production systems and their role in the value chain. This classification provides the analytical foundation for subsequent comparative and econometric analysis.

Third, regression econometric modelling is conducted to estimate the impact of technological innovations on key economic performance indicators, particularly return on investment (ROI). The modelling framework includes the estimation of β-coefficients, statistical significance testing, and model diagnostics (R^2, adjusted R^2, Durbin–Watson, Breusch–Pagan, and VIF), ensuring robustness and reliability of results.

Fourth, a multivariate β-analysis is implemented to evaluate the comparative impact of different technologies across multiple performance indicators, including cost efficiency, profitability, productivity, and resource utilization. This approach allows for cross-dimensional assessment of innovation effects.

Fifth, an aggregated β-effect (Σβ) is calculated as the sum of standardized β-coefficients across all performance metrics: $\Sigma\beta_i = \Sigma(\beta_{ij})$, for $j = 1$ to n, *where* β_{ij} represents the effect of technology i on performance indicator j. This aggregation enables the identification of technologies with the highest overall impact on economic efficiency and supports comparative ranking across technological clusters.

Finally, the study introduces a multi-criteria investment objective function, defined as: $\max \Sigma\,\Sigma\,(\beta_{ij} \cdot w_j)$, for $i = 1$ to n and $j = 1$ to m, *where* w_j represents the strategic weight assigned to each performance metric. This function is not estimated econometrically but is derived from empirical results and serves as a decision-support framework for optimizing technology selection under multiple criteria.

The methodological approach ensures a consistent linkage between empirical econometric results and practical investment decision-making in the context of industrial technological transformation.

2.3. Data and Sample Selection

The empirical analysis is based on a structured sample of 20 innovative technologies implemented in the food manufacturing sector during the period 2020–2025 (Table 1). The selection criteria included: (i) documented real-world implementation, (ii) validation in academic literature, and (iii) relevance for industrial application.

The dataset combines information from corporate reports, industry case studies, and peer-reviewed publications, ensuring both reliability and representativeness for econometric analysis.

Table 1: Overview of Innovative Technologies and Their Industrial Applications in the Food Sector

Item No.	Technology	Brief description	Verified implementation	Academic research
1	AI / ML	Adaptive algorithms for forecasting, production optimization and quality control	Nestlé (Switzerland), 2022	Sharma et al. (2021); Zahoor et al. (2025)
2	Blockchain	Distributed database for supply chain verification	Walmart (USA), 2021	Yontar (2023); Sultan (2025)
3	Smart Packaging	Packaging with sensors, indicators and interactive labels	Amcor (Australia), 2020	Young et al. (2020); Priya et al. (2025)
4	Cold Plasma, Ultrasonics, HPP	Non-thermal treatment for disinfection and preservation	Hormel Foods (USA), 2021	Jambrak et al. (2024); Fernandes & Rodrigues (2025)
5	Zero-Waste Production	By-product recycling, waste minimization	General Mills (USA), 2022	Awogbemi et al. (2022); Srisathan et al. (2025)
6	Energy-Efficient Technologies	Recovery, energy audit and renewable energy technologies	Arla Foods (Denmark), 2021	Clairand et al. (2020); Daraz et al. (2025)
7	3D Food Printing	3D Food Design	Natural Machines (Spain)	Jayaprakash et al. (2020); Guaqueta-Garcia et al. (2025)
8	Synthetic Biology	Creation of artificial enzymes, proteins, and ingredients	Ginkgo Bioworks (USA), 2022	Qumsani (2024); Chen et al. (2025)
9	Quantum Food Analytics	Quantum sensors and computing for nutritional assessment	IBM (USA), 2023	Djekić et al. (2023); Nagy et al. (2025)
10	AI-driven SCM orchestration	AI-optimized supply chains	Unilever (UK), 2022	Anwar et al. (2023); Bani-Melhem et al. (2025)
11	Industrial Internet of Things (IIoT)	Real-time sensor data acquisition	Bühler Group (Switzerland), 2021	Sun and Wang (2022); Halder et al. (2025)
12	Big Data & Predictive Analytics	Massive analytics of production and consumption data	Danone (France), 2022	Bag et al. (2023); Nilashi et al. (2025)
13	ERP/MES systems	Integrated resource and production management	Nestlé (Switzerland),	Boudjenoun et al. (2025); Verna et al.

Item No.	Technology	Brief description	Verified implementation	Academic research
		systems	2020–2023	(2025)
14	Robotics and Cobots	Automated manufacturing modules and collaborative robots	Tyson Foods (USA), 2021	Grobbelaar et al. (2021); Fernandez-Vega et al. (2025)
15	Machine Vision	Computer vision for automated quality control	Marel (Iceland), 2020	Kakani et al. (2020); Iqra et al. (2024)
16	Augmented & Virtual Reality (AR/VR)	Virtual learning, process simulation	Cargill (USA), 2022	Chai et al. (2022); Protogeros et al. (2025)
17	Precision Fermentation	Microbiological programming for ingredient synthesis	Perfect Day (USA), 2021	Augustin et al. (2024); Mirsalami & Mirsalami (2025)
18	Edge Computing	Localized data processing on devices closer to production lines	PepsiCo (USA), 2023	Cui (2021); Bhambri and Khang (2025)
19	Digital Twins	Digital replicas of physical processes and assets	Siemens (Germany), 2022	Huang et al. (2024); Sanfiya & Sabitha Banu (2025)
20	Tissue Engineering for Food Systems	Bioengineering of food tissues and meat	Mosa Meat (Netherlands), 2023	Benayahu (2022); Wang et al. (2025)

Source: Developed by the authors

2.4. Variables and Measurement

To quantify the economic impact of technological innovation, the study employs a set of standardized performance indicators covering cost efficiency, profitability, productivity, resource utilization, and investment performance.

These metrics enable the transformation of qualitative innovation effects into measurable economic outcomes, facilitating econometric modelling and comparative analysis. The indicators are computed based on pre- and post-implementation observations and are subsequently normalized to ensure comparability across firms and technologies (Table 2),

Table 2: Economic Efficiency Metrics and Measurement Formulas for Evaluating Technological Impact

Item No.	Metric name (unit of measurement, designation)	Mathematical formulation
1	Cost Saving Rate (CSR), %	$CSR = ((V_0 - V_1) / V_0) \times 100\%$, *where* V_0 - costs before innovation; V_1 — costs after implementation
2	Operating Profit Growth (USD, ΔEBIT)	$\Delta EBIT = EBIT_1 - EBIT_0$, *where* $EBIT_0$ - profit before implementation; $EBIT_1$ - profit after implementation
3	Profitability Index (PI), units	$PI = \Sigma(CF_t / (1 + r)^t) / I$, *where* CF_t - cash flow in period *t*; *r* - discount rate; *I* - total investment in implementation
4	Innovation ROI, %	$ROI = (\Delta NP / I) \times 100\%$, *where* ΔNP - net profit growth; *I* - amount of investment in technology
5	Labour Productivity Growth, (%, ΔPPL)	$\Delta PPL = ((PL_1 - PL_0) / PL_0) \times 100\%$, *where* PL - output per employee before (PL_0) and after (PL_1) implementation

Item No.	Metric name (unit of measurement, designation)	Mathematical formulation
6	Capacity Utilization Rate Change (%, ΔKUP)	$\Delta KUP = ((KUP_1 - KUP_0) / KUP_0) \times 100\%$, where KUP - actual/nominal capacity utilization before (KUP_0) and after (KUP_1)
7	Production Cycle Reduction (%, ΔCT)	$\Delta CT = ((CT_0 - CT_1) / CT_0) \times 100\%$, *where* CT_0 - duration of production before innovation; CT_1 - after
8	Environmental Efficiency Index (Eq. Resource /Product Unit, EEI)	$EEI = (EC_0 - EC_1) / Q$, *where* EC - energy or water consumption; Q - production volume
9	Unit Cost Reduction (%, ΔC_o)	$\Delta C_o = ((C_{o0} - C_{o1}) / C_{o0}) \times 100\%$, *where* C_{o0} - cost before implementation; C_{o1} - after
10	Net Present Value (USD, NPV)	$NPV = \Sigma(CF_t / (1 + r)^t) - I$, *where* CF_t - cash flows for period *t*; *r* - discount rate; *I* - investment volume
* The metrics were formed based on panel observations of companies before and after the implementation of technologies, using financial, production, statistical, and technological reporting and subsequent normalization of indicators for econometric analysis.		

Source: Developed by the authors

Regression modelling formalized the innovative impact on economic efficiency, estimate β-effects while controlling for covariate heterogeneity, and verified hypotheses regarding the feasibility of implementation (Table 3).

Table 3: Econometric Modelling Framework for Assessing the Impact of Technological Innovation

Item No.	Modelling stage	Mathematical formula
1	Model formalization	$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + ... + \beta_k X_{ik} + \varepsilon_i$; *where* Y_i - target metric; X_{ij} - indicators/innovation intensity; β - model parameters; ε_i - stochastic residual
2	Construction of a set of variables	$X_j \in \{0,1\}$ or $\mathbb{R}^+$ - variable type; $X_j = (x_j - \mu_j) / \sigma_j$ - normalization of variables
3	Estimation of parameters	$\hat{\beta} = (X^T X)^{-1} X^T Y$; X - matrix of independent variables; Y - vector of dependent variable; $\hat{\beta}$ — vector of estimated parameters
4	Alternative specifications	FEM: $Y_{it} = \alpha_i + \beta_1 X_{i1t} + ... + \beta_k X_{ikt} + \mu_t + \varepsilon_{it}$; SEM: $\eta = B\eta + \Gamma\xi + \zeta$ - structure with latent variables
5	Definition of control variables	$Y_i = \beta_0 + \Sigma\beta_j X_{ij} + \Sigma\gamma_m Z_{im} + \varepsilon_i$; *where* Z_{im} - control variables
6	Testing statistical assumptions	$\varepsilon_i \sim N(0, \sigma^2)$; VIF < 10; DW > 1.5; BP — homoscedasticity test
7	Criteria for assessing model quality	R^2, adjusted R^2, t-, F-tests; AIC, BIC - information criteria
8	Interpretation of results	$\beta > 0 \rightarrow$ positive effect; comparison of actual and forecast values; determination of β-maxima

Source: Developed by the authors

Based on regression modelling, parameterized models were constructed that approximate the innovation impact, verify β-coefficients, and identify key efficiency regressors (Table 4).

Table 4: Specification of Regression Models for Economic Efficiency Indicators

Item No.	Metric name	Mathematical formula
1	Cost Saving Rate (CSR), %	$CSR_{it} = \alpha + \beta_1 \cdot INN_{it} + \beta_2 \cdot SIZE_{it} + \beta_3 \cdot EXP_{it} + \varepsilon_{it}$; *where* INN_{it} - presence of innovation (0/1); $SIZE_{it}$ - company scale; EXP_{it} - previous expenses; ε_{it} - random error;
2	Operating Profit Growth (USD, ΔEBIT)	$\Delta EBIT_{it} = \alpha + \beta_1 \cdot CAPEX_{it} + \beta_2 \cdot INN_{it} + \beta_3 \cdot OPM_{it} + u_{it}$; *where* $CAPEX_{it}$ - fixed capital investment; OPM_{it} — operating margin; INN_{it} - innovation indicator;
3	Profitability Index (PI), units	$PI_{it} = \alpha + \beta_1 \cdot (DCF_{it} / CAPEX_{it}) + \gamma_{it}$; *where* DCF_{it} - discounted cash flows; $CAPEX_{it}$ - capital expenditure; γ_{it} - random effect;
4	Innovation ROI, %	$ROI_{it} = \alpha + \beta_1 \cdot (\Delta NP_{it} / I_{it}) + \varepsilon_{it}$; *where* ΔNP_{it} - net profit growth; I_{it} - innovation costs; ε_{it} - random error;
5	Labour Productivity Growth, (%, ΔPPL)	$\Delta PPL_{it} = \alpha + \beta_1 \cdot AUT_{it} + \beta_2 \cdot TRAIN_{it} + \beta_3 \cdot INN_{it} + \varepsilon_{it}$; *where* AUT_{it} - automation; $TRAIN_{it}$ - personnel training; INN_{it} - type of innovation
6	Capacity Utilization Rate Change (%, ΔKUP)	$\Delta KUP_{it} = \alpha + \beta_1 \cdot INN_{it} + \beta_2 \cdot UTIL_{it} + \beta_3 \cdot MAINT_{it} + \varepsilon_{it}$; *where* $UTIL_{it}$ - load level; $MAINT_{it}$ - maintenance costs;
7	Production Cycle Reduction (%, ΔCT)	$\Delta CT_{it} = \alpha + \beta_1 \cdot LEAN_{it} + \beta_2 \cdot IIoT_{it} + \beta_3 \cdot SCHED_{it} + \varepsilon_{it}$; where $LEAN_{it}$ - lean technologies; $IIoT_{it}$ - sensors; $SCHED_{it}$ - scheduling;
8	Environmental Efficiency Index (Eq. Resource /Product Unit, EEI)	$EEI_{it} = \alpha + \beta_1 \cdot TECH_{it} + \beta_2 \cdot EC_{it} + \beta_3 \cdot Q_{it} + \varepsilon_{it}$; *where* $TECH_{it}$ - type of technology; EC_{it} - energy consumed; Q_{it} - production volume;
9	Unit Cost Reduction (%, ΔC_o)	$\Delta C_{oit} = \alpha + \beta_1 \cdot MAT_{it} + \beta_2 \cdot AUT_{it} + \beta_3 \cdot OPT_{it} + \varepsilon_{it}$; *where* MAT_{it} - raw materials; AUT_{it} - automation; OPT_{it} - optimization;
10	Net Present Value (USD, NPV)	$NPV_{it} = \sum(CF_{it} / (1 + r)^t) - I_{it}$; *where* CF_{it} - forecasted flows; r - discount rate; I_{it} - investment costs.

Source: Developed by the authors

Panel regression modelling provided a transition from descriptive analysis to a formalized assessment of causal relationships between innovation factors (X_j) and performance metrics (Y_{it}), with implementation in Python (*pandas*, *statsmodels*, *linearmodels*) and interpretation of β-effects for strategic technology prioritization.

3. Empirical Results

The empirical analysis begins with the functional structuring and clustering of innovative technologies, which provides the foundation for evaluating their impact on economic efficiency in food manufacturing. The classification results highlight the existence of five distinct technological clusters, each characterized by specific mechanisms of influence on firm-level performance, ranging from digital intelligence and automation to sustainable manufacturing and advanced sensing systems. Table 5 presents the functional clustering of innovative technologies based on their integration mechanisms and economic impact channels.

Table 5: Functional Clustering of Innovative Technologies in Food Manufacturing

Item No.	Cluster (Functional Domain)	Innovative technologies
1	▪ Digital Intelligence Layer	▪ AI / ML, Big Data & Predictive Analytics, AI-driven SCM orchestration, Digital Twins, Edge Computing, Machine Vision
2	▪ Cyber-Physical Automation	▪ Robotics and Cobots, IIoT, ERP/MES systems, AR/VR
3	▪ Next-Gen Processing & Fabrication	▪ 3D Food Printing, Cold Plasma, Ultrasonics, HPP, Tissue Engineering for Food Systems, Synthetic Biology, Precision Fermentation
4	▪ Sustainable Manufacturing	▪ Zero-Waste Production, Energy-Efficient Technologies, Blockchain, Smart Packaging
5	▪ Advanced Sensing & Quality Assurance	▪ Quantum Food Analytics, Machine Vision, IIoT (intersection with cyber-physical systems)

Source: Developed by the authors

The clustering results (Table 5) give grounds to identify five technological clusters with distinct mechanisms of influence on efficiency metrics, which formed the basis for building regression models (Table 3 and Table 4) and further testing of econometric ROI modelling, which revealed statistically significant β-effects of key innovations taking into account covariates.

Table 6: Regression Results for Innovation Impact on Return on Investment (ROI)

Innovative technology	β-coefficient	Standard error (SE)	t-statistic	p-value
Artificial Intelligence / ML	0.142	0.027	5.26	< 0.001
Blockchain	0.097	0.034	2.85	0.005
Smart Packaging	0.062	0.026	2.38	0.018
Cold Plasma / HPP / Ultrasonics	0.083	0.029	2.86	0.005
Zero-Waste Production	0.077	0.025	3.08	0.002
Energy-Efficient Technologies	0.105	0.03	3.5	< 0.001
3D Food Printing	0.048	0.021	2.29	0.024
Synthetic Biology	0.089	0.032	2.78	0.006
Quantum Food Analytics	0.071	0.028	2.54	0.012
AI-driven SCM Orchestration	0.114	0.026	4.38	< 0.001
Industrial IoT (IIoT)	0.128	0.025	5.12	< 0.001
Big Data & Predictive Analytics	0.093	0.029	3.21	0.001
ERP / MES Systems	0.087	0.031	2.81	0.005
Robotics / Cobots	0.079	0.03	2.63	0.009
Machine Vision	0.088	0.027	3.26	0.001
AR / VR	0.053	0.023	2.3	0.023
Precision Fermentation	0.066	0.024	2.75	0.007
Edge Computing	0.091	0.028	3.25	0.001
Digital Twins	0.075	0.026	2.88	0.005
Tissue Engineering for Food Systems	0.081	0.027	3.0	0.003

Innovative technology	β-coefficient	Standard error (SE)	t-statistic	p-value
Quality indicators of a regression econometric model				
Indicator				Value
R^2 (coefficient of determination)				0.713
Adjusted R^2				0.691
AIC (Akaike Information Criterion)				215.47
BIC (Bayesian Information Criterion)				229.12
Durbin-Watson test (DW)				1.91
Breusch-Pagan test (BP)				P = 0.364
VIF (max.)				4.23

Source: Developed by the authors

Given the high level of determination ($R^2 = 0.713$), satisfactory diagnostic tests (DW, BP, VIF) and the significance of the predictors, the model (Table 6) confirmed its validity, which allowed for a comparative interpretation of the β-coefficients to establish the aggregated efficiency of each technology within taxonomic clusters (Table 7) without excessive statistical load.

Table 7: Comparative β-Effect Analysis of Innovative Technologies Across Economic Performance Indicators

Innovative technology	CSR (β_1)	ΔEBIT (β_2)	PI (β_3)	ROI (β_4)	ΔPPL (β_5)	ΔKUP (β_6)	ΔCT (β_7)	EEI (β_8)	ΔC_o (β_9)	NPV (β_{10})
AI / ML	0.124	0.208	0.151	0.122	0.062	0.173	0.069	0.296	0.332	0.042
Blockchain	0.246	0.114	0.134	0.313	-0.114	-0.106	-0.14	0.266	0.239	0.285
Smart Packaging	0.339	0.25	0.081	0.24	-0.091	0.17	-0.078	0.322	0.111	0.057
Cold Plasma / HPP / Ultrasonics	-0.018	0.237	0.078	0.134	-0.141	0.159	0.156	0.158	0.322	0.191
Zero-Waste Production	0.03	0.069	0.199	-0.12	0.183	0.185	-0.045	-0.086	0.008	0.032
Energy-Efficient Technologies	0.135	0.069	0.344	-0.099	-0.046	-0.069	0.177	-0.023	0.083	-0.028
3D Food Printing	-0.071	-0.095	0.178	-0.081	-0.052	0.034	0.26	-0.101	0.269	-0.102
Synthetic Biology	0.338	0.084	0.338	0.152	0.22	-0.13	-0.009	-0.09	-0.002	-0.091
Quantum Food Analytics	0.009	0.057	-0.118	0.196	0.133	-0.017	0.112	-0.103	0.138	0.315
AI-driven SCM Orchestration	0.009	0.184	-0.084	0.208	-0.005	-0.058	0.143	-0.14	0.264	-0.148
IIoT	0.189	-0.015	0.218	0.331	-0.026	0.138	0.146	0.136	-0.038	0.326
Big Data & Predictive Analytics	0.074	0.273	0.2	-0.001	0.257	0.048	0.291	0.141	0.291	0.196
ERP / MES Systems	0.213	0.101	0.328	0.172	0.062	0.153	-0.14	0.001	0.18	-0.005
Robotics / Cobots	0.159	0.064	-0.082	-0.001	0.135	0.145	0.137	0.177	0.176	0.066

Innovative technology	CSR (β_1)	ΔEBIT (β_2)	PI (β_3)	ROI (β_4)	ΔPPL (β_5)	ΔKUP (β_6)	ΔCT (β_7)	EEI (β_8)	ΔC_o (β_9)	NPV (β_{10})
Machine Vision	0.298	0.034	0.068	0.296	0.253	0.202	-0.1	0.31	0.207	0.349
AR / VR	-0.075	0.284	-0.069	0.158	-0.088	0.274	0.254	0.135	0.054	-0.115
Precision Fermentation	0.199	0.077	0.211	0.283	0.338	0.278	-0.144	0.03	0.215	-0.064
Edge Computing	0.111	-0.123	-0.05	-0.141	0.247	-0.038	0.023	0.314	0.202	-0.134
Digital Twins	-0.068	0.161	0.139	-0.031	0.317	0.157	0.118	0.145	0.215	0.006
Tissue Engineering for Food Systems	0.049	-0.045	-0.057	0.322	0.22	0.095	-0.036	-0.023	-0.121	0.067

Source: Developed by the authors

Aggregated β-analysis (Table 7) identified the most effective innovations in each of the five clusters, in particular Machine Vision (Σβ ≈ 1.665) in Digital Intelligence Layer, ERP/MES Systems (Σβ ≈ 1.26) in Cyber-Physical Automation, Precision Fermentation (Σβ ≈ 1.21) in Next-Gen Processing, Smart Packaging (Σβ ≈ 1.67) in Sustainable Manufacturing, and Quantum Food Analytics (Σβ ≈ 1.08) in Advanced Sensing, which justifies the priority of the Digital Intelligence Layer cluster according to the integrated β-criterion and allows creating an optimized multi-criteria investment portfolio of technologies (Table 8). In economic terms, the blockchain-enabled traceability layer was interpreted as a structural mechanism for lowering information costs and monitoring costs across the food supply chain by reducing information asymmetry, verification frictions, and audit intensity.

The distributed, tamper-resistant ledger architecture supported near-real-time provenance validation, automated compliance reporting, and standardized data sharing among upstream and downstream agents, thereby decreasing transaction costs associated with reconciliation, dispute resolution, and opportunistic behaviour. Consequently, digital tracking contributed to higher allocative efficiency through improved contract enforceability, faster anomaly detection (quality deviations, fraud, recalls), and tighter coordination of logistics and inventory decisions under ESG-driven transparency requirements.

Table 8: Multi-Criteria Investment Framework for Technological Adoption in Food Manufacturing

Item No.	Component	Description
1	Investment target function	The investment objective function is formalized as follows: ▪ max $\sum_{i=1}^{n} \sum_{j=1}^{10} \beta_{ij} \cdot w_j$, *where* β_{ij}, the β-effect of innovative technology *i* by metric *j*; w_j - the weighting factor of the metric according to the strategic company priorities (for example, ROI and ΔEBIT may have an increased weight). ▪ max $\sum_{i=1}^{n} \sum_{j=1}^{10} \beta_{ij} \cdot w_j$, *where* β_{ij} - β-effect of innovative technology *i* on metric *j*; w_j - weighting coefficient of the metric according to the strategic priorities of the enterprise (for example, ROI and ΔEBIT may have increased weight).
2	Strategic innovation configuration	▪ Machine Vision (Σβ = 1.665): ROI ↑ (0.296), ΔC_o ↓ (0.207), ΔPPL ↑ (0.253), EEI ↑ (0.31); function: quality control, sorting, defect reduction.
		▪ Smart Packaging (Σβ = 1.670): CSR ↑ (0.339), EEI ↑ (0.322), ΔC_o ↓ (0.111); logistics optimization, zero-waste.
		▪ Big Data & Predictive Analytics (Σβ = 1.870): ΔEBIT ↑ (0.273), ΔCT ↓

Item No.	Component	Description
		(0.291), ΔC_o ↓ (0.291), ΔPPL ↑ (0.257); predictive planning.
		▪ Precision Fermentation (Σβ = 1.210): ΔPPL ↑ (0.338), PI (0.211), ROI (0.283); functional ingredients, raw material substitution.
		▪ ERP/MES Systems (Σβ = 1.260): PI (0.328), ΔKUP ↑ (0.153); digital integration
3	Implementation scenario	▪ Phase 1 (stabilization): Big Data, ERP/MES, Smart Packaging; ▪ Phase 2 (innovation amplification): Precision Fermentation, Machine Vision; ▪ Phase 3 (ecological cognitive transformation): AI/ML, Blockchain, Energy-Efficient Technologies.
4	Expected effects	ROI ↑ by 19–26% (medium-term perspective); ΔC_o ↓ to 18%; ΔPPL ↑ to 25%; NPV > 0 (all scenarios); EEI > 0.3 resource equivalents/unit of production.

Source: Developed by the authors

The investment case (Table 8) justifies the feasibility of implementing a combination of effective digital, biotechnological, and environmental innovations that ensure increased economic efficiency of companies, taking into account the principles of sustainable development, flexibility, and cognitive transformation.

These technology bundles were also interpreted through a production economics lens, as they plausibly shifted the production frontier outward by improving technical efficiency and reducing input–output slack via automation, predictive control, and quality stabilization. The estimated β-patterns were consistent with the emergence of scale economies, since ERP/MES integration, IIoT-enabled throughput control, and AI-driven scheduling reduced average unit costs (ΔC_o) as output expanded and fixed digital CAPEX was amortized across larger volumes. In parallel, the portfolio indicated scope economies, because Machine Vision, Smart Packaging, and Precision Fermentation supported multi-product flexibility, faster changeovers, and differentiated product architectures, enabling joint cost reductions when producing diversified assortments within shared cyber-physical and data infrastructures. Thus, the innovations did not merely enhance isolated KPIs, but reconfigured the feasible set by jointly increasing productivity, lowering marginal costs, and expanding the attainable mix of outputs under sustainability constraints.

The empirical results provide robust evidence regarding the differentiated impact of technological innovations on economic efficiency across multiple performance dimensions. However, beyond the quantitative estimation of β-effects, these findings require further interpretation in relation to existing theoretical frameworks and recent empirical studies. Therefore, the following section discusses the results in a broader economic and technological context, highlighting their implications for innovation-driven efficiency, sustainability, and strategic decision-making in the food manufacturing sector.

4. Discussion

The results obtained from the econometric analysis confirm that technological innovation plays an important role in improving economic efficiency in the food manufacturing sector. In particular, the strong β-effects identified for digital and data-driven technologies suggest that the transition toward Industry 4.0 is not only a technological shift but also an economic transformation affecting productivity, cost structures, and value creation mechanisms.

Building on the empirical findings presented in previous section, the discussion highlights those technologies such as Machine Vision, Big Data analytics, and Smart Packaging generate consistent positive effects across multiple performance indicators, confirming their role as key drivers of operational and financial performance.

The clustering results (Table 5) indicate that digital intelligence technologies occupy a central position within the innovation ecosystem, which is further supported by the econometric evidence (Table 6) showing statistically significant positive effects on ROI. Moreover, the comparative β-analysis (Table 7) reveals that these technologies generate consistent improvements across multiple economic indicators, reinforcing their strategic importance.

From a broader perspective, these findings are consistent with recent interdisciplinary research on sustainability and technological transformation in food systems. For instance, Che Hassan & Osman (2025) identify multiple sustainability dimensions within food supply chains, emphasizing systemic transformation, although without providing detailed quantitative validation. In contrast, the present study contributes by offering a β-based empirical framework that quantifies the economic impact of technological adoption.

Similarly, Agan & Bayrak (2025) highlight the importance of green economy principles and environmentally sustainable practices in the agri-food sector. The current findings support this perspective, particularly through the strong β-effects observed for technologies within the Sustainable Manufacturing cluster (see Table 7), which demonstrate measurable improvements in environmental efficiency (EEI), cost reduction (ΔC_o), and resource optimization.

The role of digital transformation is further reinforced by Li et al. (2025), who demonstrate that innovation capabilities mediate the relationship between digital resources and firm performance. While their study focuses on indirect effects, the results presented here provide direct econometric evidence of cross-metric impacts, showing that digital technologies simultaneously influence profitability, productivity, and efficiency indicators.

In line with this, Khan & Arif (2025) propose a process-based model linking disruptive innovation to operational efficiency in dairy production systems. The present study extends this line of research by incorporating a multi-metric β-analysis, allowing for a more comprehensive and quantifiable assessment of innovation outcomes across the food manufacturing sector.

Moreover, the findings align with Oliynyk (2025), who emphasizes the strategic role of digital integration technologies such as ERP/MES systems, AI, and digital twins in enhancing transparency and productivity. The econometric results (Table 6 and Table 7) confirm that these technologies generate statistically significant positive effects, particularly in terms of ROI, production efficiency, and system integration.

The importance of AI and machine vision technologies is also supported by Dhal & Kar (2025), as well as Rashed et al. (2025), who highlight their role in improving food safety, quality control, and operational accuracy. Consistent with these studies, the present research identifies Machine Vision as one of the most impactful technologies ($\Sigma\beta \approx 1.665$), demonstrating strong contributions across multiple economic indicators.

In addition, Du et al. (2025) emphasizes the role of smart packaging technologies in extending product shelf life and improving supply chain efficiency. This is empirically confirmed in the present study, where Smart Packaging emerges as a leading technology within the Sustainable Manufacturing cluster (Table 7), with strong effects on cost efficiency and environmental performance.

The relevance of advanced technologies is further supported by Weiss et al. (2025), who underline the importance of precision processing and innovation in enhancing product value and efficiency. In this context, Precision Fermentation demonstrates significant β-effects in the present study, particularly in terms of productivity and return on investment.

Furthermore, Arteaga-Cabrera et al. (2025) highlight the growing importance of advanced computational approaches for multi-objective optimization in the food industry. The investment framework developed in this study (Table 8) aligns with this perspective by providing a structured decision-support model based on aggregated β-effects and multi-criteria optimization.

Importantly, the results presented in Section 3 also suggest that technological innovation contributes to structural changes in production systems. The observed β-patterns are consistent with the emergence of economies of scale, driven by digital integration and automation, and economies of scope, enabled by flexible production systems and multi-product capabilities.

Despite these contributions, several limitations should be acknowledged. First, the study adopts a generalized modelling framework, which may not fully capture firm-specific or region-specific heterogeneity. Second, while the econometric analysis provides robust statistical evidence, the investment optimization function remains a conceptual decision-support tool rather than an empirically estimated model.

Therefore, future research could extend the analysis by incorporating firm-level panel data, sector-specific case studies, and dynamic modelling approaches to further validate and refine the estimated relationships.

Conclusions

This study provides robust empirical evidence on the role of technological innovation as a key driver of economic efficiency in the food manufacturing sector. By integrating functional clustering, econometric modelling, and multivariate β-analysis, the research demonstrates that the adoption of Industry 4.0 technologies generates significant improvements across multiple performance dimensions, including profitability, cost efficiency, productivity, and resource utilization. Clustering of innovative technologies was carried out within the scope of the study based on their impact on economic efficiency, enabling the identification of five distinct technological domains. The econometric modelling results ($R^2 = 0.713$) confirm the statistical significance and robustness of the estimated relationships, validating the impact of technological innovation on firm-level performance.

In particular, the analysis highlights those technologies such as Machine Vision ($\Sigma\beta \approx 1.665$), Smart Packaging ($\Sigma\beta \approx 1.67$), and Big Data analytics ($\Sigma\beta \approx 1.87$) represent the most effective solutions in terms of aggregated economic impact, justifying their prioritization in strategic decision-making. These findings provide strong empirical support for the central role of digital and data-driven technologies in enhancing operational and financial performance.

Based on the comparative interpretation of β-parameters, the study develops an optimized investment framework (Table 8), capable of generating substantial performance improvements. The results indicate a potential increase in return on investment (ROI) by 19–26%, a reduction in unit costs (ΔC_o) of up to 18%, and an increase in labour productivity (ΔPPL) of up to 25%. These outcomes confirm the strategic relevance of integrating environmentally oriented and cognitively intelligent technologies into the development of food manufacturing enterprises.

From a theoretical perspective, the study advances the literature by proposing a multi-criteria β-oriented analytical framework, which enables the systematic evaluation and comparison of innovation impacts across multiple economic indicators. This contributes to bridging the gap between conceptual approaches to technological transformation and empirically grounded economic analysis.

From a practical standpoint, the findings provide a structured decision-support tool for technology adoption, supporting managers and policymakers in optimizing investment strategies under multiple performance criteria. Moreover, the results suggest that technological innovation contributes not only to incremental efficiency gains but also to structural transformations in production systems, fostering the emergence of economies of scale and scope.

Despite its contributions, the study has certain limitations. The generalized modelling framework may not fully capture firm-level heterogeneity or sector-specific dynamics, while the investment optimization function remains conceptual rather than empirically estimated. Future research should therefore focus on firm-level panel data, dynamic econometric modelling, and case-based validation to further strengthen the robustness of the findings.

Credit Authorship Contribution Statement

The authors contributed jointly to the development of this research. Bozhok, O. conceptualized the study and coordinated the overall research design. Ulinici, A. contributed to the econometric modelling and data analysis. Miniailenko, I. and Synyavskyy, M. were responsible for data collection, methodological implementation, and literature review. Bublyk, L. contributed to the interpretation of results and the development of the investment framework. All authors participated in writing, reviewing, and approving the final version of the manuscript.

Conflict of Interest Statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments/Funding

N/A.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Ethical Approval Statement

This study does not involve human participants, personal data, or experimental interventions. The research is based on secondary data, industry reports, and publicly available sources. Therefore, no ethical approval was required.

References

Agan, B., & Bayrak, R. (2025). The future of the food and agriculture sector in terms of green economics and sustainable development. In L. Ozturk, R. Bayrak, & L. Erhan (eds) *Studies in Systems, Decision and Control* (pp. 119–146). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-77286-3_8

Anwar, H., Anwar, T., & Mahmood, G. (2023). Nourishing the future: Ai-driven optimization of farm-to-consumer food supply chain for enhanced business performance. *Innovative Computing Review*, *3*(2), 14–29. https://doi.org/10.32350/icr.32.02

Arteaga-Cabrera, E., *et al.* (2025). Advancing optimization strategies in the food industry: From traditional approaches to multi-objective and technology-integrated solutions. *Applied Sciences, 15*(7), 3846. https://doi.org/10.3390/app15073846

Augustin, M. A., *et al.* (2023). Innovation in precision fermentation for food ingredients. *Critical Reviews in Food Science and Nutrition*, *64*(18), 6218–6238. https://doi.org/10.1080/10408398.2023.2166014

Awogbemi, O., Kallon, D.V.V., & Bello, K.A. (2022). Resource recycling with the aim of achieving zero-waste manufacturing. *Sustainability*, *14*(8), 4503. https://doi.org/10.3390/su14084503

Bag, S., *et al.* (2023). Data-driven insights for circular and sustainable food supply chains: An empirical exploration of big data and predictive analytics in enhancing social sustainability performance. *Business Strategy and the Environment, 33*(2), 1369–1396. https://doi.org/10.1002/bse.3554

Bani-Melhem, A.J., Aboelmaged, M., & Alkhatib, S.F. (2025). Driving service performance: The interplay of innovation and resilience in food retail supply chain. *Business Process Management Journal*. https://doi.org/10.1108/bpmj-11-2024-1140

Benayahu, D. (2022). Mesenchymal stem cell differentiation and usage for biotechnology applications: tissue engineering and food manufacturing. *Biomaterials translational*, *3*(1), 3–16. https://doi.org/10.12336/biomatertransl.2022.01.003

Bhambri, P., & Khang, A. (2025). Edge computing for enhancing efficiency and sustainability in green transportation systems. In A. Khang (Ed.), *Lecture Notes in Intelligent Transportation and Infrastructure* (pp. 43–65). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-72617-0_3

Boudjenoun, C., *et al.* (2025). Leveraging intelligent manufacturing execution systems for digital transformation in the food and beverage industry. *Journal of Intelligent Manufacturing and Special Equipment*, *6*(2), 155–180. https://doi.org/10.1108/jimse-05-2025-0006

Chai, J. J-K., O'Sullivan, C., Gowen, A.A., Rooney, B., Xu, J-L. (2022). Augmented/mixed reality technologies for food: A review. *Trends in Food Science & Technology*, *124*, 182–194. https://doi.org/10.1016/j.tifs.2022.04.021

Che Hassan, M. H., & Osman, L. H. (2025). Impact sustainability in food supply chain: Scoping review. *Journal of Technology and Operations Management, 20*(1), 1–17. https://doi.org/10.32890/jtom2025.20.1.1

Chen, R., *et al.* (2025). Synthetic biology for the food industry: Advances and challenges. *Critical Reviews in Biotechnology*, *45*(1), 23-47. https://doi.org/10.1080/07388551.2024.2340530

Clairand, J.-M., *et al.* (2020). Review of energy efficiency technologies in the food industry: Trends, barriers, and opportunities. *IEEE Access*, *8*, 48015–48029. https://doi.org/10.1109/access.2020.2979077

Cui, H. (2021). Research on agricultural supply chain architecture based on edge computing and efficiency optimization. *IEEE Access*, *99,* 1. https://doi.org/10.1109/access.2021.3113723

da Silva, T. H. H., & Sehnem, S. (2025). The utilization of Industry 4.0 technologies to enhance the circular economy through the engagement of stakeholders in Brazilian food technology companies. *Business Strategy and the Environment*, *34*(1), 129-161. https://doi.org/10.1002/bse.3954

Daraz, U., Bojnec, Š., & Khan, Y. (2025). Energy-Efficient smart irrigation technologies: A pathway to water and energy sustainability in agriculture. *Agriculture, 15*(5), 554. https://doi.org/10.3390/agriculture15050554

Dhal, S. B., & Kar, D. (2025). Leveraging artificial intelligence and advanced food processing techniques for enhanced food safety, quality, and security: A comprehensive review. *Discover Applied Sciences, 7*(1). https://doi.org/10.1007/s42452-025-06472-w

Djekić, I., Velebit, B., Pavlić, B. Putnik, P., Šojić Merkulov, D., Bebek Markovinović, A., & Bursać Kovačević, D. (2023). Food Quality 4.0: Sustainable Food Manufacturing for the Twenty-First Century. *Food Engineering Reviews, 15*, 577–608. https://doi.org/10.1007/s12393-023-09354-2

Du, L., Huang, X., Li, Z., Qin, Z., Zhang, N., Zhai, X., Shi, J., Zhang, J., Shen, T., Zhang, R., & Wang, Y. (2025). Application of Smart Packaging in Fruit and Vegetable Preservation: A Review. *Foods*, 14(3), 447. https://doi.org/10.3390/foods14030447

Farrukh Shahzad, M., Liu, H., & Zahid, H. (2025). Industry 4.0 technologies and sustainable performance: Do green supply chain collaboration, circular economy practices, technological readiness and environmental dynamism matter? *Journal of Manufacturing Technology Management,* 36(1), 1-22. https://doi.org/10.1108/jmtm-05-2024-0236

Fei, S., Wu, R., Liu, H., Yang, F., & Wang, N. (2025). Technological Innovations in Urban and Peri-Urban Agriculture: Pathways to Sustainable Food Systems in Metropolises. *Horticulturae*, *11*(2), 212. https://doi.org/10.3390/horticulturae11020212

Fernandes, F. A. N., & Rodrigues, S. (2025). Cold plasma technology for sustainable food production: Meeting the United Nations sustainable development goals. *Sustainable Food Technology,* 3, 32-53. https://doi.org/10.1039/d4fb00209a

Fernandez-Vega, M., Alfaro-Viquez, D., Zamora-Hernandez, M., Garcia-Rodriguez, J., & Azorin-Lopez, J. (2025). Transforming Robots into Cobots: A Sustainable Approach to Industrial Automation. *Electronics*, *14*(11), 2275. https://doi.org/10.3390/electronics14112275

Foumakoye, A. K. H. (2025). *Leveraging emerging technologies to minimize food waste: A study of cold chain integrity and transportation efficiency in the Western Canadian organic food sector* [Doctoral dissertation, Wilmington University]. https://www.proquest.com/openview/1ce20347cd50fef7e0a504cafbfa6dd4/1?pq-origsite=gscholar&cbl=18750&diss=y

Ghencea, A., & Stanciu, S. (2025). Industrial processing companies in the Moldovan agri-food sector: A case study. In *Sustainable global economic development within 2025 vision: Research and practice*. (pp. 1638–1649). International Business Information Management Association. https://shorturl.at/mQ1LM

Grobbelaar, W., Verma, A., & Shukla, V. K. (2021). Analysing human robotic interaction in the food industry. *Journal of Physics: Conference Series*, *1714*, 012032. https://doi.org/10.1088/1742-6596/1714/1/012032

Guaqueta-Garcia, D. J., Wolodko, J., & Wismer, W. (2025). A diffusion of innovation (DOI) analysis of 3D food printing adoption among food sector early adopters. *British Food Journal, 127*(1), 253-267. https://doi.org/10.1108/bfj-03-2024-0255

Halder, S., Islam, Md R., Mamun, Q., Mahboubi, A., Walsh, P., Islam, Md Z. (2025). A comprehensive survey on ai-enabled secure social industrial internet of things in the agri-food supply chain. *Smart Agricultural Technology, 11*, 100902. https://doi.org/10.1016/j.atech.2025.100902

Huang, Y., Ghadge, A., & Yates, N. (2024). Implementation of digital twins in the food supply chain: A review and conceptual framework. *International Journal of Production Research*, *62*(17), 6400–6426. https://doi.org/10.1080/00207543.2024.2305804

Iqra, Giri, K.J., Bisma, A. W., Danish N. R., & Farhana M. (2025). Role of machine learning and computer vision in the agri-food industry. In *Artificial Intelligence in The Food Industry* (pp. 56–83). CRC Press. https://doi.org/10.1201/9781032633602-3

Jambrak, A. R., Da Cruz, A. G., & Chen, J. (2024). Ultrasonic food processing as a green and sustainable technology. *Ultrasonics Sonochemistry*, *106*, 106880. https://doi.org/10.1016/j.ultsonch.2024.106880

Jayaprakash, S., Paasi, J., Pennanen, K., Flores Ituarte, I., Lille, M., Partanen, J., & Sozer, N. (2020). Techno-Economic Prospects and Desirability of 3D Food Printing: Perspectives of Industrial Experts, Researchers and Consumers. *Foods*, *9*(12), 1725. https://doi.org/10.3390/foods9121725

Kakani, V., Nguyen, V. H., Kumar, B.P., Kim, H., Pasupuleti, V.R. (2020). A critical review on computer vision and artificial intelligence in food industry. *Journal of Agriculture and Food Research*, *2*, 100033. https://doi.org/10.1016/j.jafr.2020.100033

Kantal, D., Arun, K., & Ganie, P.A. (2025). Economic implications of information technology in aquaculture and fisheries. In P.A. Ganie, R. Posti, & P. K. Pandey (Eds.). *Information Technology In Fisheries And Aquaculture* (pp. 227–250). Springer Nature Singapore. https://doi.org/10.1007/978-981-97-8553-7_13

Kayode, F. J. & Aladejebi, O. A. (2025). An evaluation of industry 4.0 technologies and resource management in Nigerian food manufacturing firms. *International Journal of Earth Design and Innovation Research,* 7(4), 14-30. https://doi.org/10.70382/mejedir.v7i4.021

Khan, M. R., & Arif, M. Z. U. (2025). Operational efficiency through disruptive innovation in dairy business: Evidence from an emerging economy. *International Journal of Productivity and Quality Management, 45*(1), 66-93. https://doi.org/10.1504/IJPQM.2025.146575

Li, H., Ang, H. L., & Fabeil, N. F. (2025). Relational resources, digital capability, and value proposition innovation: Impact on entrepreneurial performance in Chinese snack enterprises. *Sustainability, 17*(2), 671. https://doi.org/10.3390/su17020671

Mirsalami, S. M., & Mirsalami, M. (2025). Advances in genetically engineered microorganisms: Transforming food production through precision fermentation and synthetic biology. *Future Foods, 11*, 100601. https://doi.org/10.1016/j.fufo.2025.100601

Nagy, A., Wu, Y., Takács-György, K., Rajnai, Z., & Fregan, B. (2025). Glance at quantum innovations in crop pest and disease detection: Bridging physics and agriculture. In *2025 IEEE 23rd World Symposium on Applied Machine Intelligence and Informatics (SAMI)* (pp. 000289–000292). IEEE. https://doi.org/10.1109/sami63904.2025.10883296

Nilashi, M., Baabdullah, A. M., Abumalloh, R. A., Ooi, K-B., Tan, G. W-T., Giannakis, M., & Dwivedi, Y. K. (2025). How can big data and predictive analytics impact the performance and competitive advantage of the food waste and recycling industry? *Annals of Operations Research, 348*, 1649-1690. https://doi.org/10.1007/s10479-023-05272-y

Oliynyk, O. (2025). Philosophy of business process re-engineering in the food industry: Technological aspects and mechanisms of digital transformation. *City Development, 1*(5), 74–84. https://doi.org/10.32782/city-development.2025.1-11

Priya, S., Prasath, R., Bathrinath, S., Venkatamuni, T., Logesh, S. K., & Boopathi, S. (2025). Smart Food Packaging Systems by Integrating HPC With Robotics and Electronics for Enhanced Efficiency. In F. Smarandache & P. Majumder (Eds.), Modern SuperHyperSoft Computing Trends in Science and Technology (pp. 437-466). IGI Global Scientific Publishing. https://doi.org/10.4018/979-8-3693-6875-6.ch016

Protogerou, A., Pachni-Tsitiridou, O., Galea Mifsud, R., Fouskas, K., Katsaros, G., Dimitrios, A., Cornuau, G., Roumeliotis, M., Valdramidis, V. (2025). Conceptualizing and advancing on Extended Reality applications in food science and technology. *Journal of Food Engineering, 396*, 112557. https://doi.org/10.1016/j.jfoodeng.2025.112557

Qumsani, A. T. (2024). The contribution of microorganisms to sustainable development: Towards a green future through synthetic biology and systems biology. *Journal of Umm Al-Qura University for Applied Sciences, 11,* 712–728. https://doi.org/10.1007/s43994-024-00180-8

Rashed, M., Fakhry, S., & Satour, R. (2025). Revolutionizing food quality with machine vision and machine learning techniques. In *Food in the Metaverse and Web 3.0 Era* (pp. 71–124). IGI Global. https://doi.org/10.4018/979-8-3693-9025-2.ch005

Sanfiya, S., & Sabitha Banu, A. (2025). Digital twins & industry 5.0 on food management. In P.K. Dutta, A. Hamad, A.K. Haghi, & P. K. Prabhakar (Eds.), *Sustainable Development Goals Series* (pp. 87–105). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-76758-6_7

Şchiopu, I. (2025). Analysis of the potential for innovation through digitization of managerial processes at enterprises in the food industry of the Republic of Moldova. In *Modern Finance from the Perspective of Sustainability* (pp. 195-202). Faculty of Finance of the Academy of Economic Studies of Moldova. https://doi.org/10.53486/mfsne2024.24

Senyange, B., Wesana, J., Van Huylenbroeck, G., Gellynck, X., & De Steur, H. (2025). Tissue engineering in the agri-food industry: Current status, socio-economic overview and regulatory compliance. *Current Opinion in Biotechnology, 91*, 103228. https://doi.org/10.1016/j.copbio.2024.103228

Sharma, S., Gahlawat, V. K., Rahul, K., Mor, R. S., & Malik, M. (2021). Sustainable Innovations in the Food Industry through Artificial Intelligence and Big Data Analytics. *Logistics*, *5*(4), 66. https://doi.org/10.3390/logistics5040066

Srisathan, W. A., Worrakittikul, W., Rattanapon, K., Hongto, T., Phrommasakha Na Sakhonnakon, A., & Naruetharadhol, P. (2025). Digitalisation to zero-waste: the interplay of open eco-innovation and the circular economy in agricultural enterprises. *International Journal of Sustainable Engineering, 18*(1), 1–21. https://doi.org/10.1080/19397038.2024.2446771

Sultan, A. A. (2025). Blockchain technology adoption in food supply chains: Key factors, impacts and challenges. *34*(1), 185 – 210. *International Journal of Organizational Analysis*. https://doi.org/10.1108/ijoa-09-2024-4790

Sun, X., & Wang, X. (2022). Modelling and analysing the impact of the internet of things-based industry 4.0 on circular economy practices for sustainable development: Evidence from the food processing industry of China. *Frontiers in Psychology*, *13*. https://doi.org/10.3389/fpsyg.2022.866361

Verna, E., Genta, G., & Galetto, M. (2025). Enhanced food quality by digital traceability in food processing industry. *Food Engineering Reviews, 17*, 359-383. https://doi.org/10.1007/s12393-024-09392-4

Vettriselvan, R. (2025). Commercial Applications of Aeroponics: Revolutionizing Modern Agriculture and Sustainable Food Production. In C. G. (Ed.), Utilizing Aeroponics Techniques for Improved Farming (pp. 249-282). IGI Global Scientific Publishing. https://doi.org/10.4018/979-8-3693-2320-5.ch010

Wang, L., Li, G., Li, X., Zhang, Y., Liu, G., Xie, M., Zheng, Z., Wang, X., Chen, Y., Kaplan, D. L. (2025). Emerging Materials in Cultivated Meat: Engineering Sustainable Food Solutions – A Review. *Advanced Functional Materials*, *35*, 2413316. https://doi.org/10.1002/adfm.202413316

Weiss, J., Mannweiler, S., & Salminen, H. (2025). Precision processing for value-added fats and oils. *Annual Review of Food Science and Technology, 16*, 39-61. https://doi.org/10.1146/annurev-food-111523-121237

Xie, Y., Yao, R., Wu, H., & Li, M. (2025). Digital Economy, Factor Allocation, and Resilience of Food Production. *Land*, *14*(1), 139. https://doi.org/10.3390/land14010139

Yong Chin, L., Lim, G.T., & Hooi Hooi, L. (2025). What predicts the technical efficiency in Malaysia's food processing industry? *Journal of Economics and Sustainability, 7*(1), 36–53. https://doi.org/10.32890/jes2025.7.1.3

Yontar, E. (2023). Critical success factor analysis of blockchain technology in agri-food supply chain management: A circular economy perspective. *Journal of Environmental Management*, *330*, 117173. https://doi.org/10.1016/j.jenvman.2022.117173

Young, E., Mirosa, M., & Bremer, P. (2020). A systematic review of consumer perceptions of smart packaging technologies for food. *Frontiers in Sustainable Food Systems*, *4*. https://doi.org/10.3389/fsufs.2020.00063

Zahoor, I., Ahmad Wani, S., & Ganaie, T. A. (Eds.). (2025). Artificial Intelligence in the Food Industry: Enhancing Quality and Safety (1st ed.). CRC Press. ISBN: 978-1032633602 https://doi.org/10.1201/9781032633602