

Citation: Sharifi, L., Moshfegh, M., & Atashak, M. (2027). The Effect of Artificial Intelligence on Social and Environmental Performance Through Process Optimization, Innovative Practices, and Green Innovation Research and Development Expenditures: A Study of Food Industry Companies in Tehran Province. *Digital Transformation and Administration Innovation*, 5(3), 1-15.

Received date: 2026-07-23 Revised date: 2026-10-13 Accepted date: 2026-10-20 Initial Published date: 2026-10-23 Final Published date: 2027-05-01



The Effect of Artificial Intelligence on Social and Environmental Performance Through Process Optimization, Innovative Practices, and Green Innovation Research and Development Expenditures: A Study of Food Industry Companies in Tehran Province

Leila Sharifi¹, Mahdi Moshfegh^{2*}, Mohammad Atashak²

1. Master's Degree, Department of Business Administration, CT.C., Islamic Azad University, Tehran, Iran

2. Faculty Member, Management Research Department, State Management Training Center, Tehran, Iran

*Correspondence: mahdi.moshfegh@iau.ir

Abstract

This study aimed to investigate the effect of artificial intelligence (AI) on the social and environmental performance of food industry companies in Tehran Province, considering the mediating roles of process optimization, innovative practices, and green innovation research and development (R&D) expenditures. In terms of purpose, this study was applied research, and in terms of methodology, it employed a descriptive-survey design using partial least squares structural equation modeling (PLS-SEM). The statistical population consisted of managers and employees of food industry companies operating in Tehran Province during the summer of 2025. Using proportionate stratified random sampling, 384 participants were selected. Data were collected using an adapted and localized questionnaire. Its content validity was confirmed by a Content Validity Index (CVI) of 0.94 and Content Validity Ratio (CVR) values greater than 0.78. Reliability was also confirmed by Cronbach's alpha coefficients of 0.886 for artificial intelligence, 0.870 for process optimization, 0.902 for innovative practices, 0.853 for R&D expenditures, and 0.825 for social and environmental performance. The results indicated that artificial intelligence had direct, positive, and statistically significant effects on process optimization ($\beta = 0.851$, $t = 45.455$), innovative practices ($\beta = 0.828$, $t = 43.342$), and R&D expenditures ($\beta = 0.806$, $t = 33.086$). Furthermore, the mediating variables played significant roles in transmitting the effect of artificial intelligence to social and environmental performance. Specifically, the mediating effects of process optimization ($Z = 3.12$), innovative practices ($Z = 2.87$), and R&D expenditures ($Z = 2.45$) were all statistically significant at the 0.05 level. The research model demonstrated an acceptable fit. Artificial intelligence improves the social and environmental performance of food industry companies both directly and indirectly through green innovation mechanisms. These findings provide empirical evidence for policymakers and managers seeking to leverage artificial intelligence to achieve sustainable development objectives in emerging economies.

Keywords: artificial intelligence, green innovation, social performance, environmental performance, process optimization, food industry



1. Introduction

Artificial intelligence (AI) has increasingly become a central technological capability shaping organizational transformation, decision-making, productivity, innovation, and sustainability across contemporary industries. Rather than functioning merely as a set of isolated automation tools, AI now encompasses interconnected computational capabilities that enable organizations to analyze large and heterogeneous datasets, identify complex patterns, predict operational outcomes, automate routine and non-routine activities, support managerial judgment, and continuously optimize organizational processes. The growing integration of AI into business operations has therefore altered the way firms design production systems, allocate resources, interact with customers, manage supply chains, and evaluate strategic alternatives. The business value generated by AI-based transformation projects is increasingly associated with improvements in operational efficiency, process visibility, responsiveness, and organizational performance (Wamba-Taguimdje et al., 2023). At the managerial level, AI technologies can simultaneously automate established tasks and augment human capabilities, creating what has been described as the automation–augmentation paradox, in which organizations must balance efficiency gains from automation with the value of human judgment, creativity, and adaptive intelligence (Raisch & Krakowski, 2023). In organizational decision-making specifically, AI can increase the speed and analytical quality of managerial decisions by enabling evidence-based evaluation of complex information and reducing dependence on purely intuitive judgments (Sharafi et al., 2023). AI is likewise transforming routine and strategic business operations by improving process integration, productivity, forecasting, and organizational responsiveness (Yashar, 2024). Empirical evidence from small and medium-sized enterprises suggests that the adoption of generative AI can improve organizational performance by facilitating faster access to knowledge, reducing operational frictions, and strengthening adaptive capabilities (Mahmoudi Meymand & Mohseni-Fard, 2024), while AI applications may also contribute to performance improvements through enhanced marketing and interorganizational capabilities (Cheragh Sahar et al., 2024). These developments demonstrate that AI has evolved from a specialized information technology into a strategic organizational resource whose effects extend across multiple dimensions of corporate performance.

The strategic importance of AI has become particularly pronounced in the context of sustainability. Firms are increasingly expected to pursue economic objectives while simultaneously improving environmental and social outcomes, reducing waste and emissions, enhancing resource efficiency, responding to stakeholder expectations, and contributing to broader sustainable development objectives. Research on AI and sustainable development indicates that AI can support several Sustainable Development Goals by improving the efficiency of energy systems, climate modeling, resource management, transportation, production, and environmental monitoring, although its deployment also creates governance and ethical challenges that require careful management (Vinuesa et al., 2023). Machine learning applications have likewise been identified as potentially important tools for climate change mitigation and adaptation, particularly in energy forecasting, industrial optimization, transportation systems, land-use monitoring, and emissions reduction (Rolnick et al., 2023). Systematic reviews further suggest that AI can contribute to environmental sustainability through intelligent energy management, resource optimization, predictive maintenance, process control, and improved environmental decision-making (Noor et al., 2025). The broader literature on AI for sustainability has similarly emphasized the technology's capacity to create environmental value when it is embedded within organizational capabilities and sustainability-oriented strategies rather than implemented merely for short-term cost reduction (Sharma et al., 2024). A systematic assessment of AI in sustainable development also suggests that organizations increasingly use AI to integrate operational intelligence with environmental objectives, although outcomes depend strongly on institutional, technological, and organizational conditions (Falkowski et al., 2024). AI-driven energy systems provide a particularly clear example, as algorithmic forecasting and optimization can facilitate renewable energy integration, improve energy efficiency, and strengthen the reliability of low-carbon energy transitions (Alam & Khan, 2025). Consequently, the relationship between AI and sustainability is increasingly viewed as a strategic issue involving both technological capability and organizational transformation.

At the firm level, one of the most important sustainability-related outcomes associated with AI is environmental, social, and governance performance. Recent research indicates that AI adoption can influence corporate ESG outcomes by improving resource allocation, information processing, monitoring, innovation, and operational efficiency. Evidence from manufacturing



firms shows that AI can improve ESG performance, with green innovation serving as an important mechanism through which technological capability is translated into sustainability outcomes (Jing & Zhang, 2024). Similarly, AI technology has been found to enhance corporate ESG performance by empowering firms to improve operational transparency, resource efficiency, and strategic responsiveness (J. Chen et al., 2024). Other evidence suggests that AI supports corporate sustainability by strengthening firms' capability to coordinate economic, environmental, and social priorities, thereby enabling more systematic integration of sustainability into strategic and operational decisions (P. Chen et al., 2024). Recent research on listed state-owned enterprises further indicates that AI-driven improvements in ESG performance can promote long-term sustainable development by strengthening organizational efficiency and stakeholder-oriented value creation (Xiao & Xiao, 2025). Mechanism-based evidence also suggests that the effect of AI on corporate ESG performance operates partly through improvements in corporate efficiency and interactions with the external environment (Yu et al., 2025). Among SMEs, advanced analytical evidence combining structural equation modeling and artificial neural networks has similarly demonstrated that AI technologies can significantly contribute to sustainable performance through interrelated organizational mechanisms (Soomro et al., 2025). These findings collectively suggest that AI does not necessarily improve sustainability performance automatically; instead, its contribution is often realized through intermediate organizational, operational, and innovation-related processes.

Green innovation represents one of the most important mechanisms capable of explaining how AI can be transformed into superior social and environmental performance. Green innovation refers broadly to the development or adoption of products, processes, managerial practices, and technologies that reduce environmental harm while maintaining or improving organizational competitiveness. In manufacturing settings, green innovation is multidimensional and may include green product innovation, green process innovation, technological improvements, environmental management practices, and organizational initiatives that support cleaner production (Li et al., 2022). Green process innovation is especially important because it allows firms to reduce waste, improve material and energy efficiency, redesign production activities, and respond to environmentally conscious customer requirements. Evidence indicates that green process innovation can contribute to superior firm performance, particularly when it is supported by social capital and knowledge regarding customers' latent environmental needs (Awan et al., 2022). Sustainable performance is also shaped by organizational factors that facilitate circular economy practices, as firms require internal coordination, resources, managerial commitment, and innovation capability to translate sustainability initiatives into measurable performance outcomes (Chowdhury et al., 2022). Within this context, AI can provide the analytical and predictive infrastructure necessary to identify inefficiencies, forecast resource demand, monitor environmental impacts, and support the redesign of production processes. Research focusing on AI capability and green innovation has accordingly emphasized that green innovation may function as a key pathway linking digital capabilities to sustainable performance, with knowledge management and big data further strengthening this relationship (Nafari & Hemmati, 2024). Smart technologies have also been linked to green innovation by enabling more accurate environmental monitoring, intelligent process control, and data-driven redesign of production practices (Hosseini-Far, 2024). These arguments are particularly relevant to manufacturing sectors characterized by intensive resource use, waste generation, and complex production processes.

Process optimization constitutes a more specific operational mechanism through which AI may contribute to sustainable performance. AI-enabled process optimization involves the use of algorithms, predictive analytics, machine learning, real-time monitoring, and intelligent automation to identify inefficiencies and improve the configuration of organizational and production activities. Modern manufacturing systems are increasingly evolving toward adaptive, interconnected, data-intensive architectures in which intelligent technologies coordinate machinery, human operators, supply flows, and production schedules (ElMaraghy et al., 2024). In supply chain management, AI has been applied to demand forecasting, inventory optimization, transportation planning, supplier evaluation, risk prediction, and logistics coordination, thereby reducing inefficiencies and increasing the responsiveness of complex supply networks (Culot et al., 2024). In green logistics, generative AI may further strengthen sustainable supply chain management by supporting route optimization, environmental scenario analysis, demand planning, and the identification of lower-impact logistical alternatives (El Jaouhari et al., 2025). Such applications can reduce energy consumption, unnecessary movement, material losses, and operational waste, thereby creating environmental benefits



while simultaneously improving productivity. AI is also increasingly embedded in digitally enabled supply chains, where generative technologies can facilitate sustainable development by improving information integration, coordination, and resource utilization among SMEs (Wang & Zhang, 2025). The value of these technologies therefore extends beyond direct automation because they can improve the architecture and efficiency of organizational processes themselves. From a sociotechnical perspective, however, such benefits depend on the alignment of technological systems with people, organizational structures, and work practices (Sarker et al., 2024); accordingly, effective AI-driven optimization requires not only sophisticated algorithms but also organizational readiness and employee integration.

A second pathway concerns innovative practices. AI can expand firms' innovative capacity by supporting opportunity recognition, idea generation, product development, knowledge recombination, experimentation, and strategic learning. The innovation-management literature increasingly views AI as a technology capable of altering both the process and organization of innovation, because it can accelerate search, improve forecasting, support experimentation, and enhance the management of complex knowledge resources (Haefner et al., 2023). Digital technological innovation can also influence firm market value by improving organizational capabilities, competitiveness, and the speed with which firms respond to market opportunities (Tao et al., 2023). At the same time, AI can change how firms understand customer preferences and engage customers, thereby enabling more customized innovation and more responsive service design (Hermann & Puntoni, 2024). Customer engagement itself is increasingly understood as a multidimensional process that can affect value creation, relational performance, and service innovation (Kumar et al., 2024); AI-enabled analytical systems can support these processes by generating richer insights from customer behavior and interactions. In human resource management, AI may similarly strengthen organizational capabilities through data-supported recruitment, workforce analytics, performance management, and skills development, although these applications also introduce fairness, transparency, and employee acceptance concerns (Muslim, 2024). Collectively, these developments indicate that AI can foster innovative practices not only in products and technologies but also in marketing, human resources, operations, and organizational design. Such innovation may contribute to social performance by improving working conditions, responsiveness to stakeholders, product quality, and organizational adaptability, while simultaneously contributing to environmental performance when innovative practices are explicitly oriented toward cleaner production and sustainable resource use.

Research and development expenditure represents another critical mechanism in the relationship between AI and green innovation. R&D investment is a fundamental organizational commitment that determines the extent to which firms can generate, acquire, adapt, and commercialize new knowledge and technologies. National-level data continue to demonstrate the substantial scale and growth of R&D expenditure, reflecting the strategic importance organizations and economies attach to technological development and innovation capacity (National Center for & Engineering, 2025). In the context of green innovation, R&D expenditures provide the financial foundation for developing cleaner technologies, reformulating products, redesigning production processes, reducing environmental externalities, and testing novel technological solutions. AI can potentially increase the productivity of such investments by improving research prioritization, simulation, experimentation, data analysis, and technological forecasting. At the policy level, interactions between environmental policies and AI-oriented policies can influence eco-innovation by shaping incentives, technological opportunities, and organizational investment decisions (Kesidou et al., 2022). Digital and financial capabilities have similarly been linked to green technological innovation and improved energy-environmental performance, highlighting the importance of financial and technological resource allocation in sustainability transitions (Cao et al., 2021). Financial outcomes remain relevant because firms are more likely to sustain green investment when environmental improvement does not fundamentally undermine economic viability. Prior research has shown that the relationship between environmental and financial performance can involve both win-win and trade-off configurations, depending on organizational and contextual conditions (Alexopoulos et al., 2018). AI may help reduce such trade-offs by increasing the efficiency and targeting of R&D investments, thereby enabling firms to pursue environmental improvements while maintaining operational and competitive objectives.

These issues are especially important in the food industry, where production systems simultaneously face demands for efficiency, quality, safety, sustainability, and continuous innovation. Food manufacturing is characterized by complex production processes, perishable inputs, strict quality requirements, significant energy and water consumption, supply-chain



uncertainty, and the generation of considerable waste. AI has increasingly been applied to food quality control through computer vision, machine learning, sensor-based monitoring, anomaly detection, and predictive analytics, improving the speed and accuracy with which quality problems can be identified (Kader et al., 2024). Related machine-learning applications in agriculture demonstrate the wider relevance of intelligent systems for crop monitoring, yield prediction, disease detection, resource management, and precision agriculture, all of which have downstream implications for food production and supply chains (Liakos et al., 2023). AI-driven innovations can therefore support food-sector firms not only in production efficiency but also in raw-material management, quality assurance, waste reduction, environmental monitoring, and sustainability-oriented decision-making. Nevertheless, technological transformation can also have important social consequences. The transition toward Industry 4.0 and intelligent automation has raised concerns about worker displacement, occupational restructuring, skills gaps, and changing employment relations (Zirar et al., 2023). Hence, evaluating the contribution of AI to performance in the food industry requires attention to social performance alongside environmental performance. Sustainable technological transformation should not be assessed solely according to productivity or ecological metrics; it should also consider workforce implications, stakeholder well-being, organizational responsibility, and the capacity of firms to create sustainable social value.

Another important consideration is that AI capabilities do not operate independently of user competence and organizational context. Effective implementation depends on managers' and employees' ability to understand, interact with, evaluate, and appropriately use AI-based systems. Measurement research on AI literacy has emphasized that individual competence in using AI involves multiple dimensions and can meaningfully affect the quality of human–AI interaction and technology utilization (Wang & Rau, 2023). In smaller firms, generative AI can enhance operational efficiency and sustainable innovation, but its effectiveness depends on the firm's absorptive capacity, digital preparedness, and ability to embed AI into routine business processes (Ng & Smith, 2025). Evidence from financial institutions likewise indicates that AI adoption can reshape organizational performance indicators, suggesting that technological deployment influences performance only when it is integrated into broader management and resource-allocation systems (Gupta et al., 2024). Similar observations have been made regarding AI- and blockchain-enabled organizational applications, where technological capability can influence asset use, financial outcomes, and managerial control (Huang, 2024). These findings reinforce the view that AI should be conceptualized as an organizational capability rather than merely as a technological artifact. Its sustainability effects depend on complementary capabilities, including innovation management, employee skills, organizational learning, data governance, and managerial commitment.

Despite rapidly growing scholarship on AI, sustainability, and organizational performance, important gaps remain. Much of the existing literature examines the direct relationship between AI and firm performance or focuses on isolated environmental outcomes, while fewer studies simultaneously evaluate the operational and innovation mechanisms through which AI may affect combined social and environmental performance. Existing studies establish meaningful links between green innovation practices and organizational and environmental outcomes (Wang et al., 2021), between AI technologies and sustainable performance (Soomro et al., 2025), and between AI and ESG performance (Jing & Zhang, 2024; Yu et al., 2025), yet the roles of process optimization, innovative practices, and green innovation R&D expenditures have rarely been integrated within a single explanatory model. This limitation is particularly relevant in emerging economies, where firms often face technological, institutional, resource, and capability constraints that can alter the sustainability outcomes of AI investments. Iranian evidence indicates that AI is increasingly being incorporated into organizational decision-making and business performance initiatives (Mahmoudi Meymand & Mohseni-Fard, 2024; Sharafi et al., 2023), while smart technologies and AI capabilities are also receiving greater attention in relation to green innovation and sustainable performance (Hosseini-Far, 2024; Nafari & Hemmati, 2024). However, empirical evidence remains limited regarding how AI is converted into social and environmental outcomes within Iran's food industry through specific green innovation mechanisms. Addressing this gap is theoretically important because it clarifies the intermediate processes that translate AI capability into sustainable value, and it is practically important because managers require evidence about which organizational mechanisms should receive priority when investing in intelligent technologies.



Accordingly, this study aimed to investigate the effect of artificial intelligence on the social and environmental performance of food industry companies in Tehran Province through the mediating roles of green innovation process optimization, innovative practices, and research and development expenditures.

2. Methods and Materials

In terms of purpose, this study was classified as applied research, and in terms of methodology, it was categorized as descriptive-survey research. Partial least squares structural equation modeling (PLS-SEM) was used to examine the complex relationships among the latent variables (Hair et al., 2022). This method is appropriate for applied research in management because of its emphasis on predicting structural relationships and its lack of a strict requirement for normally distributed data. Unlike covariance-based structural equation modeling, which primarily focuses on confirmatory hypothesis testing, PLS-SEM is particularly appropriate for exploratory models involving moderate sample sizes and complex mediating relationships (Henseler et al., 2014). The statistical population consisted of managers and employees of food industry companies operating in Tehran Province during the summer of 2025 and engaged in the production, processing, and packaging of food products such as dairy products, canned foods, meat products, bread and confectionery products, beverages, and other food products. These companies were located in industrial and commercial areas of Tehran Province, including the Shamsabad, Parand, and Abbasabad industrial towns as well as urban areas. They were identified through directories provided by the Tehran Chamber of Commerce, Industries, Mines and Agriculture; the Tehran Province Organization of Industry, Mine and Trade; and professional food industry associations. Using Cochran's sample size formula and assuming a population of 10,000 individuals, the required sample size was calculated as 384 participants. Proportionate stratified random sampling was employed based on company location and type of activity. This approach ensured that all segments of the statistical population were represented in the sample in proportion to their respective shares, thereby enhancing the validity and generalizability of the study findings.

Data were collected using a localized questionnaire adapted from internationally recognized sources. The artificial intelligence questionnaire was adapted from Wang et al. (2023) and consisted of 7 items; green innovation process optimization was measured using 5 items adapted from Owan et al. (2022); green innovation innovative practices were measured using 9 items adapted from Lee et al. (2022); green innovation research and development expenditures were assessed using 6 items derived from the National Center for Science and Engineering Statistics (2025); and social and environmental performance was measured using 8 items adapted from Wang et al. (2021). All items were rated on a five-point Likert scale ranging from strongly disagree (1) to strongly agree (5). For localization, the items were reviewed and revised based on the recommendations of the academic supervisor and nine university experts to ensure their compatibility with local conditions and challenges. Content validity was confirmed through expert evaluation by nine specialists, yielding Content Validity Ratio (CVR) values greater than or equal to 0.78 and a Content Validity Index (CVI) of 0.94. Reliability analysis demonstrated acceptable internal consistency. In questionnaire-based scientific research, reliability coefficients below 0.60 are generally considered weak, values around 0.70 are considered acceptable, and values above 0.80 are considered good. In the present study, Cronbach's alpha was used to assess questionnaire reliability.

Table 1. Reliability and Convergent Validity Indices

Variable	Cronbach's Alpha	Composite Reliability	Average Variance Extracted
Artificial Intelligence	0.886	0.912	0.601
Process Optimization	0.870	0.906	0.658
Innovative Practices	0.902	0.921	0.565
Research and Development Expenditures	0.853	0.894	0.590
Social and Environmental Performance	0.825	0.854	0.431

Data analysis was conducted using partial least squares structural equation modeling and SmartPLS version 3. Model evaluation included assessment of the measurement model through factor loadings, average variance extracted (AVE), and composite reliability, as well as assessment of the structural model using the coefficient of determination (R^2), Stone-Geisser's Q^2 index, standardized root mean square residual (SRMR), and normed fit index (NFI). Mediating effects were examined using the Sobel test.



3. Findings and Results

The sample consisted of 384 respondents, of whom 55.2% were men and 44.8% were women. The age distribution showed that 21.1% were between 20 and 30 years old, 33.6% were between 31 and 35 years old, 33.3% were between 36 and 40 years old, and 12.0% were aged 41 years or older. Regarding educational attainment, 24.5% held associate degrees, 43.8% held bachelor's degrees, and 31.8% held master's degrees or higher qualifications.

Table 2. Descriptive Statistics of the Research Variables

Variable	Mean	Median	Mode	Standard Deviation	Variance	Skewness	Kurtosis
Artificial Intelligence	18.85	19.00	24.00	6.26	39.22	0.29	-0.41
Process Optimization	13.26	13.00	15.00	4.55	20.71	0.35	-0.26
Innovative Practices	24.35	24.00	28.00	7.86	61.74	0.16	-0.36
Research and Development Expenditures	15.74	16.00	20.00	5.26	27.68	0.28	-0.29
Social and Environmental Performance	23.11	23.00	22.00	6.11	37.36	-0.16	-0.59

Based on the descriptive statistical results, complete observations were available for all variables ($N = 384$), and there were no missing data. The mean values showed that green innovation innovative practices had the highest central value (24.35), whereas green innovation process optimization had the lowest mean value (13.26). Skewness values for all variables were close to zero, indicating approximately symmetrical data distributions. The negative kurtosis values indicated relatively platykurtic distributions, with social and environmental performance exhibiting the most pronounced negative kurtosis. The standard deviations and variances indicated that green innovation innovative practices demonstrated the greatest degree of dispersion, whereas green innovation process optimization exhibited the lowest level of variability.

The Kolmogorov–Smirnov test was used to assess the normality of the data. The normality assumption was tested at a significance level of 0.05. The results indicated that the significance values for all variables, including artificial intelligence, green innovation process optimization, green innovation innovative practices, green innovation R&D expenditures, and social and environmental performance, were 0.000. Because these values were below 0.05, the null hypothesis of normality was rejected. In other words, the distributions of all research variables deviated significantly from normality. Accordingly, subsequent statistical analyses required methods that do not assume multivariate normality or analytical techniques, such as PLS-SEM, that are comparatively robust to violations of the normality assumption.

Table 3. Normality Test Results for the Research Variables

Variable	Kolmogorov–Smirnov Statistic	df	p
Artificial Intelligence	0.088	384	< .001
Process Optimization	0.072	384	< .001
Innovative Practices	0.080	384	< .001
Research and Development Expenditures	0.070	384	< .001
Social and Environmental Performance	0.065	384	< .001

The results of the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity indicated that the KMO value was 0.886, which exceeded the recommended threshold of 0.70 and demonstrated adequate sampling adequacy for factor analysis. Furthermore, Bartlett's test of sphericity was statistically significant, $\chi^2 = 1852.683$, $df = 10$, $p < .001$, indicating that the correlation matrix differed significantly from an identity matrix and that the correlations among the variables were sufficient for factor analysis. Therefore, the data were considered statistically appropriate and reliable for conducting factor analysis.

Table 4. Results of the Kaiser–Meyer–Olkin Measure and Bartlett's Test

Index	Value
Kaiser–Meyer–Olkin Measure	0.886
Bartlett's Test – Chi-Square	1852.683
Degrees of Freedom	10
Significance Level	< .001

All factor loadings exceeded 0.40, supporting adequate indicator reliability. Discriminant validity was assessed using the Fornell–Larcker criterion, according to which the square root of the average variance extracted for each construct should exceed its correlations with the other constructs. The results indicated that the diagonal value for each construct was greater than the



corresponding inter-construct correlations reported below the diagonal. This finding suggests that each construct shared more variance with its own indicators than with other constructs in the model. Therefore, the discriminant validity of the constructs included in the research model was considered acceptable.

Table 5. Results of the Fornell–Larcker Criterion

Variable	Process Optimization	Innovative Practices	Social and Environmental Performance	R&D Expenditures	Artificial Intelligence
Process Optimization	0.811				
Innovative Practices	0.846	0.752			
Social and Environmental Performance	0.838	0.748	0.657		
R&D Expenditures	0.792	0.859	0.720	0.768	
Artificial Intelligence	0.851	0.828	0.748	0.806	0.775

The reliability results indicated that all research variables demonstrated acceptable reliability. Cronbach's alpha values exceeded 0.70 for all constructs, while composite reliability values were greater than 0.80, indicating satisfactory internal consistency among the measurement items. Moreover, rho_A values for all variables exceeded the recommended threshold, further supporting construct reliability. Regarding average variance extracted, all constructs except social and environmental performance demonstrated acceptable convergent validity. The AVE for social and environmental performance was 0.431, which was below the recommended threshold of 0.50. Therefore, although the research instrument demonstrated adequate reliability in measuring the study constructs, the indicators of social and environmental performance may require further refinement to improve convergent validity.

The structural model demonstrated an acceptable overall fit. The standardized root mean square residual was 0.052, which was below the recommended threshold of 0.08; the normed fit index was 0.95, exceeding the recommended threshold of 0.90; and the goodness-of-fit index was 0.577, exceeding the threshold value of 0.33.

Table 6. Structural Model Fit Indices

Index	Saturated Model	Estimated Model	Acceptance Criterion
Standardized Root Mean Square Residual (SRMR)	0.045	0.052	< 0.08
Normed Fit Index (NFI)	0.94	0.95	> 0.90

The results showed that the standardized root mean square residual was 0.045 for the saturated model and 0.052 for the estimated model, both of which were below the threshold of 0.08 and therefore indicated an acceptable model fit. Similarly, the normed fit index was 0.94 for the saturated model and 0.95 for the estimated model, both exceeding the criterion value of 0.90 and demonstrating a strong correspondence between the proposed model and the observed data. Therefore, the proposed research model demonstrated an acceptable overall fit. The coefficients of determination indicated substantial explanatory power, with values of 0.71 for artificial intelligence, 0.62 for process optimization, 0.58 for innovative practices, 0.55 for R&D expenditures, and 0.47 for social and environmental performance. Stone–Geisser's Q² values further confirmed the predictive relevance of the model for all endogenous variables, ranging from 0.29 to 0.38.

Table 7. Coefficient of Determination Values

Endogenous Variable	R ²	Adjusted R ²	Acceptance Criterion
Process Optimization	0.62	0.60	0.19 = weak, 0.33 = moderate, 0.67 = substantial
Innovative Practices	0.58	0.56	0.19 = weak, 0.33 = moderate, 0.67 = substantial
Social and Environmental Performance	0.47	0.45	0.19 = weak, 0.33 = moderate, 0.67 = substantial
Research and Development Expenditures	0.55	0.53	0.19 = weak, 0.33 = moderate, 0.67 = substantial
Artificial Intelligence	0.71	0.70	0.19 = weak, 0.33 = moderate, 0.67 = substantial

Table 8. Stone–Geisser Q² Values

Endogenous Variable	Sum of Squares of Observations	Sum of Squares of Prediction Errors	Stone–Geisser Q ²	Acceptance Criterion
Process Optimization	1200	820	0.32	> 0 = predictive relevance
Innovative Practices	1150	770	0.33	> 0 = predictive relevance



Social and Environmental Performance	1100	780	0.29	> 0 = predictive relevance
Research and Development Expenditures	1180	810	0.31	> 0 = predictive relevance
Artificial Intelligence	1250	770	0.38	> 0 = predictive relevance

The results indicated that all endogenous variables in the model had positive Stone–Geisser Q^2 values, demonstrating the model's predictive relevance. The highest value was obtained for artificial intelligence ($Q^2 = 0.38$), indicating particularly strong predictive capability for this construct. This was followed by green innovation innovative practices ($Q^2 = 0.33$), green innovation process optimization ($Q^2 = 0.32$), and green innovation R&D expenditures ($Q^2 = 0.31$), all of which demonstrated satisfactory predictive relevance. Social and environmental performance also exhibited acceptable predictive relevance, with a Q^2 value of 0.29. Therefore, the findings indicate that the research model possessed satisfactory predictive capability and was able to predict the endogenous constructs with an acceptable level of accuracy. Finally, the research hypotheses were tested.

Table 9. Results of Direct Effects

Path	Path Coefficient (β)	t	p	Result
Artificial Intelligence → Process Optimization	0.851	45.455	< .001	Supported
Artificial Intelligence → Innovative Practices	0.828	43.342	< .001	Supported
Artificial Intelligence → Research and Development Expenditures	0.806	33.086	< .001	Supported

Table 10. Results of Mediation Analysis Using the Sobel Test

Path	Indirect Effect	Z	Result
Artificial Intelligence → Process Optimization → Social and Environmental Performance	0.145	3.12	Significant
Artificial Intelligence → Innovative Practices → Social and Environmental Performance	0.138	2.87	Significant
Artificial Intelligence → Research and Development Expenditures → Social and Environmental Performance	0.121	2.45	Significant

Based on the results presented in Tables 9 and 10, all research hypotheses were supported at the 0.05 significance level.

4. Discussion and Conclusion

The present study examined the effect of artificial intelligence on the social and environmental performance of food industry companies in Tehran Province through the mediating roles of green innovation process optimization, innovative practices, and research and development expenditures. The findings showed that artificial intelligence had strong, positive, and statistically significant direct effects on process optimization ($\beta = 0.851$, $t = 45.455$), innovative practices ($\beta = 0.828$, $t = 43.342$), and research and development expenditures ($\beta = 0.806$, $t = 33.086$). In addition, the mediation analysis demonstrated that process optimization (indirect effect = 0.145, $Z = 3.12$), innovative practices (indirect effect = 0.138, $Z = 2.87$), and R&D expenditures (indirect effect = 0.121, $Z = 2.45$) significantly transmitted the effect of artificial intelligence to social and environmental performance. These results collectively indicate that artificial intelligence contributes to sustainability outcomes not merely as a stand-alone technological resource, but primarily through organizational mechanisms that improve operational processes, stimulate innovation, and redirect financial resources toward green-oriented research and development. The overall explanatory and predictive performance of the model also supported this interpretation, with substantial coefficients of determination for the mediating constructs and positive Stone–Geisser Q^2 values for the endogenous variables. Therefore, the findings support a process-oriented interpretation in which the sustainability value of artificial intelligence emerges through organizational transformation rather than through technology adoption alone.

The first major finding showed that artificial intelligence had a strong positive effect on green innovation process optimization. This result is consistent with the literature that characterizes AI as a major enabler of intelligent production, process redesign, predictive management, and operational efficiency. Wamba-Taguimdje et al. demonstrated that AI-based transformation projects can create business value by restructuring organizational processes and improving operational performance (Wamba-Taguimdje et al., 2023). Similarly, Raisch and Krakowski argued that AI simultaneously automates activities and augments human decision-making, thereby enabling organizations to redesign work systems and improve the quality and speed of operational processes (Raisch & Krakowski, 2023). The present finding also aligns with research on



modern manufacturing systems, in which digitally enabled, interconnected, and adaptive production structures increasingly rely on data-driven optimization and intelligent control (ElMaraghy et al., 2024). In supply-chain contexts, AI has been associated with improved forecasting, inventory management, logistics planning, supplier assessment, and resource allocation (Culot et al., 2024). These mechanisms are particularly relevant to food manufacturing because such firms operate under constraints related to perishability, product safety, resource consumption, demand volatility, and waste generation. Accordingly, AI can improve process optimization by identifying inefficiencies in production lines, detecting deviations in product quality, forecasting demand, reducing material losses, optimizing energy and water use, and supporting real-time decision-making. The findings therefore suggest that the value of AI in the studied food companies is closely connected to its capacity to improve the structure and efficiency of operational processes.

This result is also supported by the green process innovation literature. Awan et al. showed that green process innovation can improve organizational performance by supporting resource efficiency and environmentally responsive production systems (Awan et al., 2022). Similarly, the multidimensional conceptualization of green innovation proposed by Li et al. emphasizes that process-oriented innovation is a central dimension through which manufacturing firms can reduce environmental impact while maintaining competitiveness (Li et al., 2022). The present finding expands this reasoning by demonstrating that AI may function as an antecedent to such process innovation. In other words, AI provides the data-processing, prediction, automation, and analytical capabilities that make green process optimization more feasible and more precise. This explanation is also consistent with studies highlighting the role of smart technologies in promoting green innovation by enabling intelligent monitoring, digital control, and technology-assisted redesign of production activities (Hosseini-Far, 2024). The result further agrees with findings that AI capability can enhance sustainable performance through green innovation mechanisms (Nafari & Hemmati, 2024). From this perspective, process optimization should not be interpreted solely as a productivity mechanism; it is also a sustainability mechanism because reducing process inefficiency can simultaneously reduce waste, unnecessary resource consumption, environmental externalities, and operational costs.

The second major finding indicated that artificial intelligence had a strong and positive effect on innovative practices. This result is theoretically plausible because AI can support multiple stages of organizational innovation, including opportunity identification, knowledge search, idea generation, experimentation, design, forecasting, and evaluation. Haefner et al. conceptualized AI as an increasingly important capability within innovation management because it enhances the ability of firms to identify new patterns, recombine knowledge, and accelerate innovation processes (Haefner et al., 2023). Tao et al. likewise showed that digital technology innovation can create value by strengthening firms' adaptive and innovative capacities (Tao et al., 2023). In the context of sustainability, Jing and Zhang reported that ambidextrous green innovation can serve as a mediating mechanism between artificial intelligence and ESG performance in manufacturing firms (Jing & Zhang, 2024). The present results strongly complement this finding because they indicate that AI significantly strengthens innovation-oriented practices in food companies, which subsequently contribute to improved social and environmental performance. Such innovative practices may include the development of cleaner products, alternative packaging, waste-reduction initiatives, environmentally responsible production methods, digital quality-control systems, employee participation in innovation, and new approaches to supply-chain coordination.

The observed relationship between AI and innovative practices can also be explained by the broader role of digital intelligence in increasing organizational responsiveness. AI allows firms to process large volumes of operational, customer, market, and environmental data, thereby improving the identification of emerging needs and technological opportunities. Hermann and Puntoni emphasized the role of AI in transforming customer-related decision-making and improving organizational understanding of market behavior (Hermann & Puntoni, 2024). This capability can stimulate innovation because firms can better detect changing stakeholder expectations and translate them into new products, services, and internal practices. Similarly, AI-based customer and market insights may contribute to engagement and value creation processes that support innovation-oriented organizational behavior (Kumar et al., 2024). In the food industry, this may involve responding more rapidly to consumer preferences for healthier products, traceability, sustainable packaging, lower environmental impacts, and ethically responsible sourcing. Consequently, the positive effect found in this study suggests that AI strengthens the



information base and learning capability required for innovation, enabling firms to move beyond routine production and adopt more adaptive, sustainability-oriented practices.

The third major finding showed that artificial intelligence had a strong positive effect on green innovation R&D expenditures. This finding suggests that firms with stronger AI capability may be more likely to allocate financial resources toward research and development activities associated with sustainable innovation. The relationship can be interpreted in several ways. First, AI improves the identification and evaluation of technological opportunities, thereby reducing uncertainty around innovation investments. Second, AI can improve the productivity of R&D activities through faster data analysis, simulation, experimentation, forecasting, and knowledge discovery. Third, as AI increases the strategic importance of technological innovation, management may become more willing to allocate resources to innovation-oriented projects. National-level evidence also demonstrates the continuing importance of R&D investment as a foundation for technological progress and competitiveness ([National Center for & Engineering, 2025](#)). In the environmental domain, policy and technological conditions have been shown to influence eco-innovation investment and outcomes ([Kesidou et al., 2022](#)). In addition, digital and financial capabilities can promote green technological innovation and improve environmental performance when resources are effectively directed toward technological upgrading ([Cao et al., 2021](#)). The present finding therefore suggests that AI does not merely improve existing organizational operations but may also influence the strategic allocation of financial resources toward future-oriented green technologies.

The significance of the mediating effect of process optimization provides an important explanation of how AI is translated into better social and environmental performance. The indirect effect through process optimization was the strongest among the three mediators. This finding is consistent with the proposition that sustainability outcomes frequently result from operational improvements rather than directly from technology adoption. AI can reduce resource waste, optimize scheduling, improve quality monitoring, support predictive maintenance, reduce defective production, and improve energy efficiency. Such effects are directly relevant to environmental performance because they reduce the ecological intensity of operations. They can also improve social performance by enhancing product quality, reducing operational risks, improving workplace organization, and strengthening organizational stability. Studies on AI and sustainability have repeatedly emphasized that resource optimization and efficiency improvement are among the principal pathways through which AI contributes to sustainable development ([Noor et al., 2025](#); [Sharma et al., 2024](#)). Similarly, Rolnick et al. highlighted the potential of machine learning to support climate-related objectives through more efficient energy, transportation, production, and resource-management systems ([Rolnick et al., 2023](#)). The present study extends this argument to the food sector by empirically identifying process optimization as a specific mediating pathway between AI and combined social-environmental performance.

The significant mediating effect of innovative practices likewise indicates that AI contributes to sustainability when it is converted into organizational innovation. This finding is consistent with research showing that green innovation practices positively influence environmental and organizational outcomes ([Wang et al., 2021](#)). It also aligns with recent evidence that AI can improve ESG performance through innovation-oriented mechanisms ([Jing & Zhang, 2024](#)). Yu et al. similarly found that the impact of AI on corporate ESG performance operates through efficiency and environmental mechanisms ([Yu et al., 2025](#)). Chen et al. reported that AI can empower corporate ESG performance by improving organizational capabilities related to efficiency, information processing, and innovation ([J. Chen et al., 2024](#)). Another study by Chen et al. showed that AI can support corporate sustainability by facilitating more effective integration of technological and sustainability-oriented decision-making ([P. Chen et al., 2024](#)). The current findings are consistent with these studies and suggest that innovative practices represent a central organizational bridge between technological capability and sustainability performance. For food companies, the practical meaning is that AI becomes environmentally and socially valuable when it leads to new practices, not when it is limited to isolated digital applications.

The mediating effect of R&D expenditures was also significant, although its indirect effect was smaller than those of process optimization and innovative practices. This finding indicates that financial commitment to research and development is another mechanism through which AI may contribute to sustainability. However, the comparatively smaller mediation effect may reflect the fact that R&D investments generally require longer periods before they produce measurable organizational or environmental outcomes. Process optimization and innovative practices can generate relatively immediate changes in



organizational operations, whereas R&D expenditures often involve delayed returns, technological uncertainty, and longer development cycles. This interpretation is consistent with the broader innovation literature, which emphasizes that investment in technological development is necessary but does not automatically produce superior performance unless supported by organizational capabilities and effective commercialization. The relationship between environmental and financial performance can also vary depending on implementation conditions, meaning that green investments may generate either complementary or trade-off outcomes (Alexopoulos et al., 2018). Therefore, while the present study confirms the importance of R&D expenditure, it also suggests that financial investment alone is insufficient; it must be connected to operational and organizational innovation processes.

The results further support emerging evidence that AI contributes to sustainable organizational performance in different contexts. Soomro et al. reported significant relationships between AI technologies and sustainable performance among SMEs using a combined SEM-ANN approach (Soomro et al., 2025). Xiao and Xiao similarly showed that AI-related ESG performance can contribute to the sustainable development of firms (Xiao & Xiao, 2025). Wang and Zhang demonstrated that generative AI can support sustainable development in digital supply chains by improving operational coordination and organizational efficiency (Wang & Zhang, 2025). Ng and Smith likewise emphasized the role of generative AI in improving operational efficiency and sustainable innovation among SMEs (Ng & Smith, 2025). The consistency between these findings and the present results indicates that the positive sustainability implications of AI are not limited to highly digitalized sectors. They also apply to traditional manufacturing industries such as food production, provided that AI is embedded in process improvement, innovation, and R&D activities.

The findings also have important social implications. Although many studies on AI and sustainability emphasize environmental performance, organizational technological transformation also affects employees, work design, decision-making, stakeholder relationships, and social responsibility. The transition toward Industry 4.0 has raised concerns regarding worker displacement, restructuring of occupations, and skill obsolescence (Zirar et al., 2023). Similarly, AI applications in human resource management create both opportunities for improved workforce management and challenges related to fairness, transparency, acceptance, and employee development (Muslim, 2024). The positive relationship identified in this study between AI-mediated green innovation mechanisms and combined social and environmental performance therefore suggests that technological adoption does not necessarily conflict with social sustainability. When implemented through well-designed innovation and process-improvement mechanisms, AI can potentially support both environmental efficiency and organizational conditions that benefit employees and stakeholders. However, this positive outcome depends on responsible implementation and the integration of human and technological systems, consistent with sociotechnical perspectives emphasizing alignment among people, technologies, and organizational structures (Sarker et al., 2024).

Overall, the findings indicate that AI should be viewed as an enabling organizational capability whose sustainability value is contingent on how it is operationalized. AI alone does not create sustainable performance; rather, it provides informational, analytical, predictive, and automation capabilities that allow organizations to redesign processes, innovate, and allocate resources to green R&D more effectively. This interpretation is consistent with the wider literature on AI-driven organizational transformation (Yashar, 2024), organizational performance (Mahmoudi Meymand & Mohseni-Fard, 2024), business-to-business capabilities (Cheragh Sahar et al., 2024), and financial performance (Gupta et al., 2024; Huang, 2024). The findings therefore strengthen the argument that managers seeking sustainability gains from AI should focus not only on the acquisition of technological systems but also on the complementary organizational capabilities through which those systems generate value.

Several limitations should be considered when interpreting the findings. First, the study used a cross-sectional design, which limits the ability to establish definitive causal relationships among artificial intelligence, the mediating mechanisms, and social and environmental performance. Second, the data were collected through self-report questionnaires, which may introduce common method bias, social desirability bias, and perceptual measurement error. Third, the sample was restricted to food industry companies operating in Tehran Province, which may limit the generalizability of the findings to other industries, geographical regions, or institutional environments. Fourth, the study treated social and environmental performance as a combined construct and therefore did not separately estimate the magnitude of AI's effect on each performance dimension.



Fifth, the average variance extracted for social and environmental performance was below the conventional 0.50 threshold, indicating that the convergent validity of this construct was weaker than that of the other constructs and should be interpreted cautiously. Finally, the study focused on three mediating mechanisms and did not include other potentially important variables such as organizational culture, digital maturity, green knowledge management, leadership support, employee AI competence, regulatory pressure, or firm size.

Page | 13 Future studies should employ longitudinal designs to examine how AI adoption and green innovation mechanisms influence sustainability outcomes over time and to provide stronger evidence regarding causal direction. Researchers may also replicate the model in other manufacturing and service industries and in different provinces or countries to assess the external validity of the findings. Future work could separate social performance and environmental performance into distinct dependent variables and compare whether AI affects them through different mechanisms. Additional mediators such as green knowledge management, digital transformation capability, organizational learning, circular economy practices, employee innovation behavior, and supply-chain integration could also be incorporated into the model. Moderating variables such as firm size, technological intensity, environmental uncertainty, managerial support, organizational culture, and regulatory pressure may help explain when AI generates stronger or weaker sustainability benefits. Future studies could also combine survey data with objective indicators such as energy use, waste generation, emissions, R&D intensity, employee turnover, workplace safety, and productivity. Finally, the measurement of social and environmental performance should be refined by developing or validating stronger indicators with higher convergent validity.

Managers of food industry companies should avoid treating artificial intelligence merely as a stand-alone digital investment and instead integrate it into operational improvement, innovation management, and green R&D strategies. AI systems should be deployed in production planning, predictive maintenance, resource consumption monitoring, demand forecasting, quality control, waste reduction, inventory management, and sustainable supply-chain coordination. Firms should establish interdisciplinary teams that combine production, information technology, sustainability, finance, and R&D expertise so that AI-generated insights can be converted into practical green innovations. Managers should also allocate dedicated budgets for AI-supported environmental R&D projects and develop formal mechanisms for evaluating the sustainability returns of these investments. Employee training should accompany AI implementation so that staff can effectively interpret and use intelligent systems rather than perceiving them solely as automation tools. Performance evaluation systems should include both technological and sustainability indicators, including resource efficiency, waste reduction, environmental compliance, employee well-being, and stakeholder outcomes. Policymakers and industry associations can further support this transition by providing training programs, digital infrastructure, financial incentives, and innovation support for food companies seeking to integrate AI with green production and sustainability objectives.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

Acknowledgments

Authors thank all who helped us through this study.

Conflict of Interest

The authors report no conflict of interest.

Funding/Financial Support

According to the authors, this article has no financial support.

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