AI-driven Transformation in Coffee Agribusiness: a Systematic Review of Innovation, Efficiency, and Sustainability Interactions and Future Research Potential

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Abstract. This study aims to map the impact of digital transformation driven by AI technology in the coffee industry, focusing on three key aspects: efficiency, innovation, and sustainability, as well as their interactions. Through a systematic review of hundreds of existing studies, this research identifies patterns in AI technology adoption and uncovers future research opportunities to expand its applications, including its effects on SMEs and smallholder farmers. This article employs a Systematic Literature Review (SLR) to examine the latest developments in AI technology adoption within the coffee industry. The primary focus is to map the benefits of AI in enhancing operational efficiency, driving product and process innovation, and strengthening sustainability. Additionally, this study explores the interconnections among these three aspects in shaping a more inclusive and sustainable digital ecosystem for industry stakeholders. The review indicates that while AI adoption in the coffee industry continues to expand, studies examining the interactions between efficiency, innovation, and sustainability remain scarce. Among the articles reviewed, 33 key benefits of AI technology implementation in the coffee sector were identified. The mapping reveals that efficiency is the most dominant aspect, followed by innovation and then sustainability. Additionally, many of these benefits overlap, creating opportunities for further research to optimize AI applications in the industry.

Keywords: AI and coffee, Digital transformation, Efficiency, Innovation, Sustainability, Systematic literature review.

1 Introduction

Despite the growing interest in artificial intelligence (AI) across various industrial sectors, its application in the coffee industry – as a key component of the food sector – remains underexplored. This gap arises due to several challenges, including the limited expertise of human resources [1], the experimental nature of most existing AI models, which restricts their scalability in real-world contexts [2], and inadequate technological accessibility for a broader user community [3]. Furthermore, many studies focus on

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specific coffee varieties or geographic regions [4], while current AI systems often lack adaptability to diverse operational needs and contexts.

However, the coffee industry serves as a crucial pillar in the global agri-food system, supported by its significant economic value [5] and its vital social impact on millions of smallholder farmers worldwide. According to the International Coffee Organization (2023), global coffee consumption is projected to increase by 2.2% in 2023/24, reaching 177.0 million bags. This growth is driven by modern lifestyle trends and rising consumption in developing countries [6].

Simultaneously, this sector faces multifaceted challenges that necessitate innovative solutions. These challenges include volatile global price dynamics [7], disruptions caused by climate change [8]; [9], pesticide resistance [10, 11], and resource competition [12] – all of which threaten the industry's long-term sustainability. Amid these pressures, AI presents transformative potential to redefine supply chain management paradigms across the coffee value chain.

Extensive efforts have been made to reinforce the economic and social benefits of coffee in line with global Agri-Tech 4.0 trends. These initiatives align with urgent global agendas, such as the Sustainable Development Goals (SDGs), specifically zero hunger, which encompasses food security [13], poverty alleviation (SDG 1) [14], and sustainable agriculture (SDGs 2) [15], as well as calls for innovation [16]. Such initiatives are critical for the coffee sector, which struggles with climate volatility and market dynamics while aiming to reduce poverty and achieve sustainable farming practices.

Previous studies have explored AI's role in various coffee industry applications. A systematic literature review on AI adoption in supply chain management highlights its ability to enhance operational efficiency and sustainability through predictive analytics and process automation [17]. Research on specialty versus conventional coffee bean quality for hot and cold brews [18] demonstrates AI's capability to standardize quality through sensory profiling and physicochemical analysis.

Efforts to identify relevant AI applications for SMEs, particularly in the agricultural sector, highlight infrastructure barriers and the need for cost-effective models [19]. Moreover, investment in Industry 4.0 technologies is encouraged to strengthen competitiveness and efficiency for small agribusiness enterprises [20]. A review of AI applications for sustainable solid waste management [21] further underscores its potential in optimizing resource use and minimizing waste.

Literature on AI-driven coffee product development encompasses machine learning for bean classification [22], precision agriculture techniques for enhancing sustainability [23], roast level detection [24], and AI-supported coffee rust disease monitoring [25]. While interest in artificial intelligence (AI) within agricultural systems continues to rise, no systematic research to date has comprehensively explored its transformative impact on the coffee industry, particularly in relation to the three key pillars of innovation, efficiency, and sustainability.

This study addresses this critical gap by conducting the first systematic literature review (SLR) that synthesizes AI's role in coffee agribusiness through the lens of these interconnected pillars. By mapping current AI applications – from precision farming to sustainable supply chain optimization – this research establishes a foundational framework for guiding future technology development within the sector. Additionally, this study highlights unexplored domains, providing actionable pathways for researchers, policymakers, and industry stakeholders to prioritize innovation while balancing economic and environmental interests.

Thus, the research questions posed in this study are as follows:

QR1. How does AI technology contribute to the transformation of the coffee industry across three key aspects – innovation, efficiency, and sustainability – and how do these aspects interact?

QR2. What are the primary research gaps and opportunities for future studies to advance AI applications in this industry?

The objective of this research is to provide industry stakeholders with insights into the digital transformation enabled by AI technology, specifically within the framework of efficiency, innovation, and sustainability. Additionally, this study seeks to identify future research opportunities to enhance AI's role in the coffee industry within this framework.

2 Method

This systematic literature review (SLR) employs a web-based platform known as the Watase Uake System (https://www.watase.web.id/home/index.php). This specialized system provides a structured procedure and facilitates the execution of systematic literature reviews while exclusively offering international articles indexed in Scopus to date. The methodology follows these steps:

1. Identifying keywords, inclusion/exclusion criteria, and research limitations.
2. Screening articles for relevance.
3. Retrieving selected articles and addressing potential exclusions.
4. Reviewing the titles, abstracts, and keywords of shortlisted articles.
5. Mapping pathways and extracting data from each selected study; and
6. Analyzing classifications, creating tables, and generating relevant visualizations.

The visualization of the process and results obtained is presented in Fig. 1. Fig. 1 displays a flow diagram illustrating the data collection process in the systematic literature review on artificial intelligence (AI) technology and the coffee industry, following the PRISMA 2020 reporting guidelines available in the Watase Uake System. This process is designed to ensure transparency, reproducibility, and rigor in selecting relevant studies.

During the identification stage, the keyword "artificial intelligence AND coffee" was used to search for records in the primary database, Scopus, yielding 136 records. Additionally, an automated search tool was employed to find supplementary records from the period 2016 to 2025, resulting in 21 records, which were immediately excluded for failing to meet inclusion criteria such as topic irrelevance, duplication, or low quality. The process also included the removal of 42 additional records for various reasons, including classification under Tier Q1, Q2, Q3, and Q4, as well as unavailability of full text. Furthermore, 6 records without abstracts were excluded.

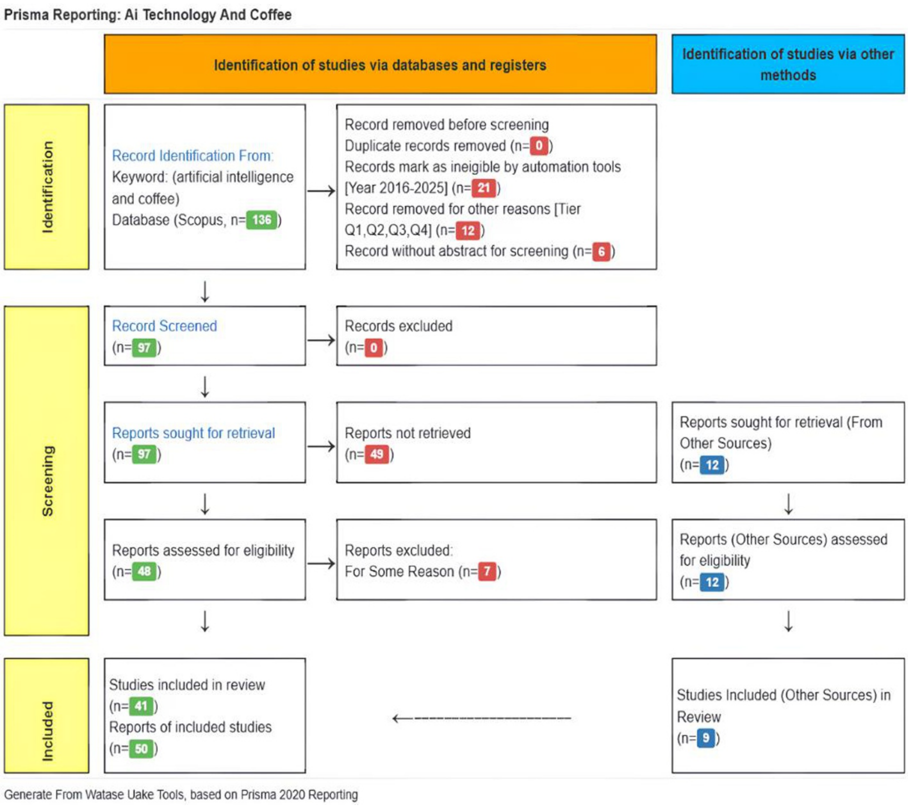

Fig. 1. Flowchart of the review process using the PRISMA method

During the screening stage, a total of 102 records entered the selection process. In this phase, 11 records were excluded for failing to meet strict inclusion criteria, such as methodological irrelevance or lack of focus on the coffee value chain.

The eligibility stage involved the evaluation of 101 reports, of which 54 reports could not be accessed due to availability limitations. However, 6 reports were successfully retrieved from supplementary sources such as open repositories or institutional websites, though they were still indexed in Scopus. Among the reports assessed for eligibility, 47 reports were evaluated, but 7 reports were excluded due to low quality or duplication. Additionally, 12 reports from other sources were also assessed for eligibility.

Ultimately, 41 studies were included in this systematic literature review. Out of 43 reports related to the included studies, 9 additional studies were obtained from external sources not recorded in the Watase Uake System, bringing the total number of analyzed articles in this study to 50.

This study identifies, evaluates, and synthesizes the latest research on the application of artificial intelligence (AI) in the coffee industry, with a primary focus on three key aspects: innovation, efficiency, and sustainability. In the context of an increasingly competitive industry, the adoption of cutting-edge technologies such as AI is becoming ever more crucial to ensuring business continuity and growth.

Relevant studies are categorized into these three main aspects, each providing insights into how AI has revolutionized the coffee industry to date:

First, research on innovation in the coffee industry through artificial intelligence (AI) highlights the crucial role of this technology in creating new products and enhancing consumer experiences. However, barriers to innovation remain, particularly within the coffee sector, as noted by [23]. These challenges include infrastructure readiness [26] and the limited application of AI to specific coffee varieties within certain countries [27].

Second, studies on operational efficiency following AI adoption indicate that this technology is expected to significantly reduce costs and processing time in production. Yet, paradoxically, rather than achieving greater efficiency, AI implementation still entails high investment and operational costs [28].

Third, the relationship between AI and sustainability principles in the coffee supply chain is gaining increasing attention. Nonetheless, the economic sustainability of small and medium-sized enterprises (SMEs) faces regulatory uncertainty, leading to hesitation in adopting AI [29]. Other challenges include a lack of trust, knowledge, and resources [30]. Additionally, the high costs associated with AI platforms pose further obstacles [31].

This three-pronged approach is expected not only to enhance the competitiveness of the coffee industry but also to contribute positively to environmental and societal well-being. To analyze these studies, this research follows systematic steps in the literature review (SLR), including defining the research questions, conducting a structured literature search, and applying strict inclusion and exclusion criteria. A total of 50 studies were collected, thereby meeting the SLR qualification criteria, which require a minimum of 40 articles [32].

The selected studies are then classified based on three key aspects, each aligned with the benefits generated, emphasizing the positive impact of AI technology on daily life. This process ensures that the findings are not only objective but also well-structured, significantly contributing to further research advancements in this field.

3 Results and Discussion

It is also essential to examine the growth trends in the number of articles discussing artificial intelligence (AI) technology in the coffee industry from 2016 to 2025. As illustrated in Fig. 2, the data reflects a significant increase in publications, highlighting the growing interest among researchers, industry professionals, and academics in applying AI across various aspects of the coffee sector.

This growth initially began with a relatively low number of articles in 2015, followed by a gradual increase until 2019. By 2020, the number of articles started to rise more rapidly, continuing to grow significantly compared to earlier years. This trend suggests that AI has become a central focus in the development and innovation of the coffee industry, driven by advancements in increasingly sophisticated and accessible technologies, as well as the greater availability of data for AI development and implementation.

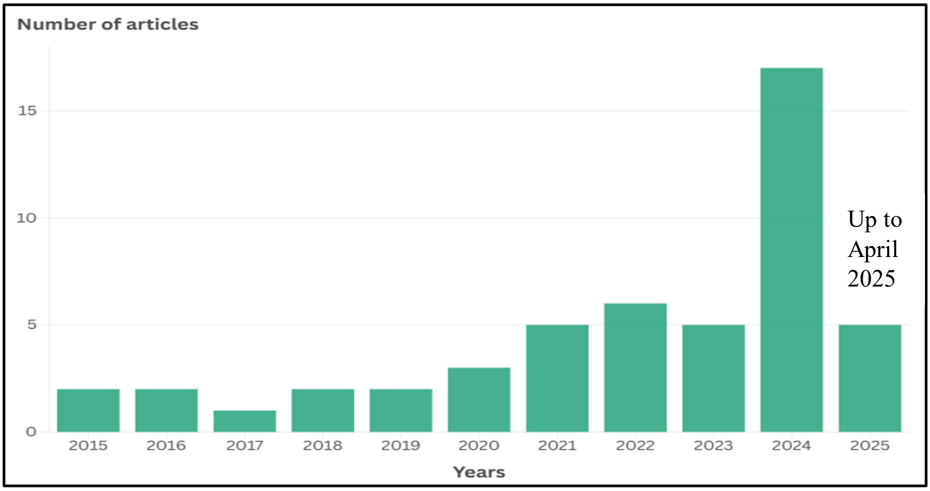

Fig. 2. Trends in AI research for coffee industry (2015–2025)

The increasing number of articles can also be linked to structural changes in the global coffee industry. *First*, AI is increasingly recognized as an effective tool for enhancing operational efficiency, optimizing supply chains, and improving final product quality. *Second*, challenges such as climate change, price fluctuations, and dynamic market demands drive the coffee industry to seek innovative solutions, where AI can play a transformative role. *Third*, the growing availability of structured and open datasets, alongside advancements in machine learning and digital image processing, facilitate research and AI applications in the coffee industry.

This dynamic shift suggests that AI is not only a promising research area but also a catalyst for transforming the coffee sector towards greater sustainability and efficiency. Fig. 3 illustrates the distribution of research on AI technology in the coffee industry across various countries. The image indicates that certain nations– such as Brazil – have made particularly strong contributions in this field.

Additionally, research involving international collaborations demonstrates significant cross-border participation. Other countries, including South Korea, Taiwan, and Indonesia, also exhibit considerable contributions, albeit to a lesser extent. This phenomenon reflects high global interest and participation in AI applications within the coffee sector, reinforcing AI's potential to reshape the industry on an international scale.

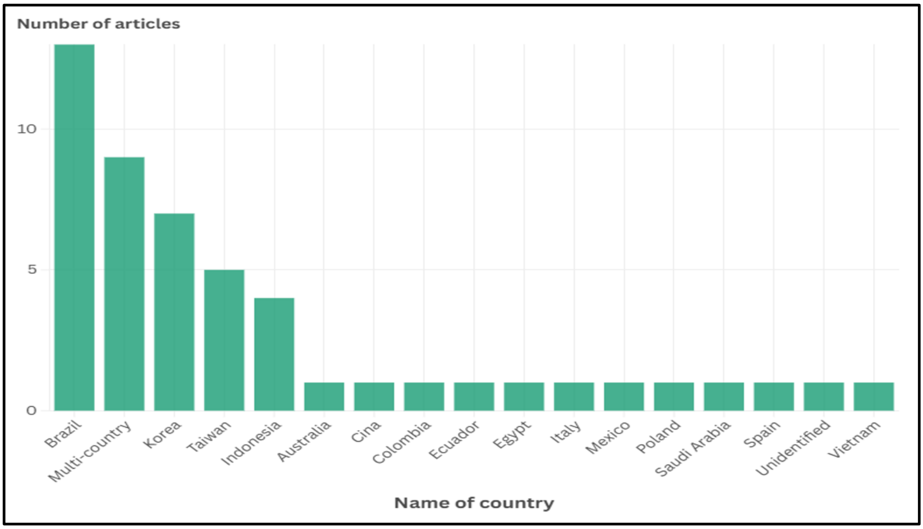

Fig. 3. AI technology research on coffee products by country

Fig. 4 presents a word cloud mapping key terms in the application of artificial intelligence (AI) within the coffee agribusiness sector. Larger text size represents more relevant or frequently occurring topics such as "Artificial Intelligence," "Machine Learning," "Deep Learning," and "Computer Vision." These terms reflect research trends and AI applications in coffee agroindustry, including quality assessment, precision agriculture, and production process innovation through automation. The word cloud illustrates how AI contributes to advancing the coffee agribusiness landscape, offering insights into dominant themes shaping technological development in this field.

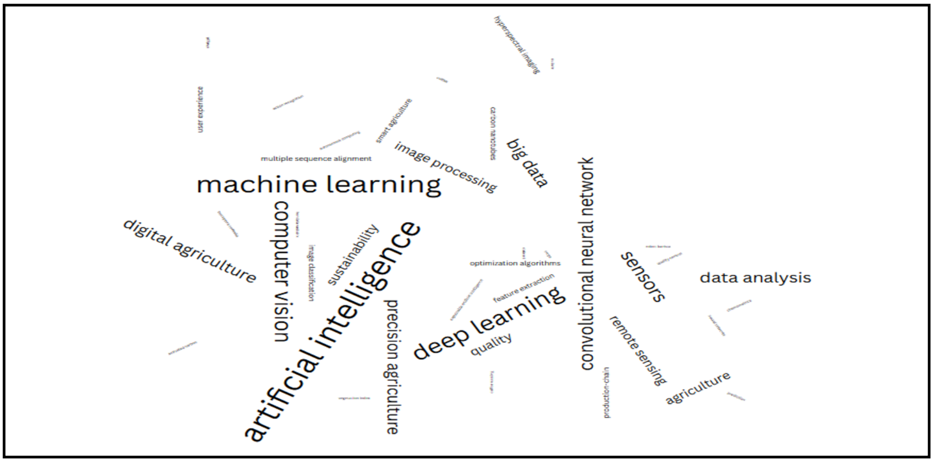

Fig. 4. Key concepts driving AI innovation in coffee production

Recent advancements in academic research on AI applications in the coffee industry have revealed significant developments in the field. Table I provides a summary of the top 10 studies and applications of artificial intelligence (AI) in coffee agribusiness, ranked based on various academic indicators such as journal tier (Q1, Q2, Q3, Q4), authors, year of publication, citation count, and article title. These studies represent the most influential contributions in the AI-driven transformation of the coffee sector, selected according to the highest citation counts and their presence in prestigious international journals (Q1/Q2).

The studies examined in Table 1 explore diverse AI applications, ranging from harvest yield prediction based on soil fertility properties to coffee bean classification using computer vision systems. Additionally, research has focused on the development of smart sensors and renewable energy solutions derived from coffee waste, reflecting AI's expanding role in optimizing production, improving efficiency, and enhancing sustainability. These findings underscore the increasing integration of AI in the coffee industry, demonstrating its potential to drive innovation and reshape traditional agricultural practices.

The dominance of topics such as plant disease detection, precision agriculture, and food processing innovations reflects global research priorities aimed at improving efficiency, sustainability, and coffee production quality through AI-driven solutions. These articles serve not only as a theoretical foundation for further research but also as practical solutions that can be adapted across various stages of the coffee supply chain.

Table 1 presents the ranking of the 10 most-cited articles on AI applications in coffee production and processing. These articles have been published in various high-tier journals (Q1 and Q2), exploring diverse AI applications such as yield prediction, coffee bean classification, disease detection, and the utilization of coffee waste for energy devices.

The top-ranked article, published in Computers and Electronics in Agriculture by Kouadio et al. in 2018, has 147 citations and focuses on predicting Robusta coffee yields based on soil fertility properties. Other studies cover various topics, including computer vision for coffee bean classification, nano-power generation from coffee waste, and machine learning algorithms for predicting pest and disease outbreaks in Coffea arabica. This table provides a comprehensive overview of how AI is applied across different aspects of coffee production and processing, highlighting emerging research trends and evolving applications in this field.

Table 2 presents a compilation of 33 benefits of AI technology in the coffee industry, structured across three core dimensions: innovation, efficiency, and sustainability. Each benefit is accompanied by relevant authors and publication years, along with detailed explanations that justify its classification within a specific category. This organization provides a comprehensive overview of how AI contributes to technological advancements, improving industry processes while fostering more sustainable practices. AI plays a critical role in driving innovation through the development of new methodologies, enhancing efficiency by optimizing operational workflows and resource allocation, and promoting sustainability through reduced environmental impact and the adoption of eco-friendly approaches.

Table 1. Top 10 most cited articles on artificial intelligence applications in coffee production and processing

Rank	Journal	Tier	Authors	Cites	Title
1	Computers and Electronics in Agriculture	Q2	[33]	147	Artificial intelligence approach for the prediction of Robusta coffee yield using soil fertility properties.
2	Journal of Food Engineering	Q1	[34]	96	A computer vision system for coffee beans classification based on computational intelligence techniques.
3	Nano Energy	Q1	[35]	65	Deformable, resilient, and mechanically durable triboelectric nanogenerator based on recycled coffee waste for wearable power and self-powered smart sensors.
4	International Journal of Biometeorology	Q2	[36]	61	Machine learning algorithms for forecasting the incidence of Coffea arabica pests and diseases.
5	Biosystems Engineering	Q2	[37]	60	Deep learning architectures for semantic segmentation and automatic estimation of severity of foliar symptoms caused by diseases or pests.
6	Sustainability	Q1	[38]	53	Untact: Customer's acceptance intention toward robot barista in coffee shop.
7	Applied Sciences	Q2	[39]	38	Deep-Learning-Based Defective Bean Inspection with GAN-Structured Automated Labelled Data Augmentation in Coffee Industry.
8	CIRP Annals	Q1	[40]	37	Intelligent Kano classification of product features based on customer reviews.
9	Scientia Agricola	Q2	[41]	35	Genomic prediction of leaf rust resistance to Arabica coffee using machine learning algorithms.
10	Agriculture	Q2	[42]	33	Deep Learning Ensemble-Based Automated and High-Performing Recognition of Coffee Leaf Disease.

By consolidating insights from various academic studies, stakeholders can quickly assess current trends and emerging directions in AI applications within coffee agribusiness. This structured approach enables more informed decision-making and strategic planning, equipping industry leaders with the necessary insights to maximize innovation, improve operational efficiency, and enhance sustainable growth. As AI continues to evolve, its expanding role in the coffee industry underscores its potential to drive transformative advancements and reshape traditional agricultural practices.

Table 2. Compilation of AI benefits in the coffee industry based on innovation, efficiency, and sustainability aspects

No	Compilation of AI Benefits	Authors	Aspects	Rationale
1	Automated Social Failure Analysis in Product Design	[43]	Innovation	Introduces a novel method of integrating AI into product design to analyze social failures, offering a new perspective not previously documented.
2	Predictive Modelling and Marker-assisted Selection	[41]; [44]	Innovation	Combines innovative predictive models with marker-assisted selection to enhance breeding efficiency.
3	Non-destructive Estimation Using Artificial Neural Networks	[45]; [46]	Innovation, Sustainability	Offers an innovative method for estimation that also supports sustainable farming practices by preserving plant integrity.
4	Enhanced Coffee Quality and Sensory Profiles	[47]; [48]	Innovation, Sustainability	Introduces innovative methods for enhancing coffee quality while supporting sustainable farming practices.
5	Optimized Pesticide Application and Resource Efficiency	[49]; [50]	Efficiency, Sustainability	Enhances the efficiency of pesticide use and resource allocation while reducing environmental impact.
6	Quality Control, Waste Reduction, and Supply Chain Optimization	[34]; [51]; [44]	Efficiency, Sustainability	Focuses on improving quality control and reducing waste in the supply chain.
7	Process Optimization and Quality Preservation	[52]; [53]	Efficiency, Sustainability	Improves process efficiency while maintaining product quality and reducing waste.
8	Data Processing Optimization and Crop Monitoring	[46]	Efficiency, Sustainability	Reduces network loads and improves crop monitoring.
9	Plantation Monitoring and Decision Support	[54]	Innovation, Efficiency	Enhances decision-making through innovative plantation monitoring techniques.
10	ICT and AI for Enhanced Collaborative Performance	[55]; [56]	Innovation, Efficiency	Combines innovative ICT and AI techniques to improve collaborative performance.
11	Automated Quality Control in Food Industry	[39]; [57]	Efficiency	Improves quality control processes through automation.
12	Enhanced Consistency and Efficiency in Coffee Brewing	[58]; [38]	Efficiency	Enhances the consistency and efficiency of coffee brewing processes.

No	Compilation of AI Benefits	Authors	Aspects	Rationale
13	Automated Interactions to Enhance User Experience	[59]; [60]	Efficiency	Boosts customer satisfaction through efficient interactions.
14	Image Classification, Pattern Recognition, and Agricultural Automation	[61]; [62]	Efficiency	Saves time and labor in agricultural processes.
15	Improved Decision-making Accuracy and Consistency in Personnel Selection	[63]	Efficiency	Enhances the accuracy and consistency of personnel selection.
16	Enhanced Decision-making for Industrial Automation	[64]	Efficiency	Reduces downtime and boosts production through better decision-making.
17	Market Analysis and Price Prediction	[65]; [66]; [67]	Efficiency	Improves business decision-making with accurate predictions.
18	Customer Satisfaction and Experience Enhancement	[68]; [40]	Efficiency	Enhances customer loyalty and satisfaction.
19	Efficiency Improvement, Cost Reduction, and Quality Consistency	[56]; [69]	Efficiency	Lowers operational costs and improves product consistency.
20	Customer Experience and Operational Efficiency Enhancement	[38]; [60]	Efficiency	Boosts customer satisfaction and operational efficiency.
21	Pest and Disease Prediction and Management	[36]; [70]	Innovation, Efficiency, Sustainability	Combines innovation with efficiency and sustainability in managing pests and diseases.
22	Disease Resistance Prediction and Disease Detection Using AI	[71]; [72]; [73]: [42]; [44]	Innovation, Efficiency, Sustainability	Utilizes new technology for disease prediction and detection, improving efficiency and supporting ecosystem health.
23	Yield Prediction and Agricultural Optimization	[33]; [62]	Innovation, Efficiency, Sustainability	Uses predictive models to improve agricultural yields and efficiency.
24	Disease Diagnosis Improvement and Resource Optimization	[73]; [33]	Innovation, Efficiency, Sustainability	Enhances diagnosis accuracy and resource use efficiency.
25	Information Management and Decision Support	[67]; [74]	Innovation, Efficiency	Supports better decision-making using data.
26	Health Monitoring and Human-machine Interaction	[75]; [55]	Innovation, Sustainability	Enhances workplace health and safety with environmentally friendly interactions.

No	Compilation of AI Benefits	Authors	Aspects	Rationale
27	Energy Management and Eco-awareness	[76]; [66]	Sustainability	Reduces energy consumption and raises environmental awareness.
28	Roasting Process Optimization and Sensory Profile Enhancement	[22]; [44]	Innovation, Sustainability	Enhance product quality and support sustainable farming.
29	Disease Detection and Efficiency Improvement	[44]; [61]	Efficiency	Enhances the efficiency of disease detection and decision-making.
30	Pest and Disease Management and Prediction	[36]; [70]	Innovation, Efficiency, Sustainability	Uses models to manage pests and diseases, improving efficiency and ecosystem health.
31	Data-driven Decision-making and Support	[67]; [74]	Innovation, Efficiency	Supports better decision-making using data.
32	Non-destructive Evaluation and Remote Monitoring of Coffee Grinder Wear	[77]	Innovation, Efficiency	New technology for monitoring machine conditions without stopping operations.
33	Process Optimization, Quality Control, and Automation	[44]; [53]	Efficiency	Enhances production process efficiency and consistency.

This study identifies the transformational role of artificial intelligence (AI) in the coffee industry through three key pillars: innovation, efficiency, and sustainability. Findings indicate that AI has paved the way for innovation, including real-time monitoring systems for coffee bean quality and the development of smart sensor-based products, such as FlavourScape AI, which provides instant flavor profile analysis of coffee. The application of computer vision for coffee bean classification and machine learning for predicting plant diseases (e.g., coffee leaf rust) has enhanced farmers' accuracy and responsiveness, as demonstrated by [42].

In terms of efficiency, AI has successfully reduced production costs and minimized waste through process automation, such as AI-driven irrigation systems that optimize water use and weed detection systems that replace chemical herbicides. [49] illustrate that neural networks and remote sensing can precisely adjust fertilizer and pesticide applications, reducing environmental impact while improving crop yield. [39] also highlights AI's role in accelerating coffee bean quality inspections through automated data augmentation.

On the sustainability front, AI contributes to eco-friendly agricultural practices, such as coffee waste management, which transforms waste into value-added products (e.g., compost or renewable energy) and water conservation through precision agriculture. Studies by [78] and [36] highlight how predictive algorithms enhance crop resilience against climate change, while [79] underscores AI's potential in processing organic waste into sustainable materials. However, high investment costs and regulatory uncertainty remain barriers to AI adoption, particularly for SMEs.

The Venn diagram in Fig. 5 presents the distribution of AI's 33 benefits across three dimensions: Innovation, Efficiency, and Sustainability. It highlights unique contributions specific to each dimension and overlapping advantages shared across two or all three areas. Notably, while some AI applications clearly drive innovation or enhance sustainability, many generate synergies across multiple dimensions. For instance, five benefits are shared between Innovation and Efficiency, four between Innovation and Sustainability, and four between Efficiency and Sustainability. Importantly, five benefits impact all three dimensions, emphasizing AI's comprehensive potential to revolutionize coffee agriculture.

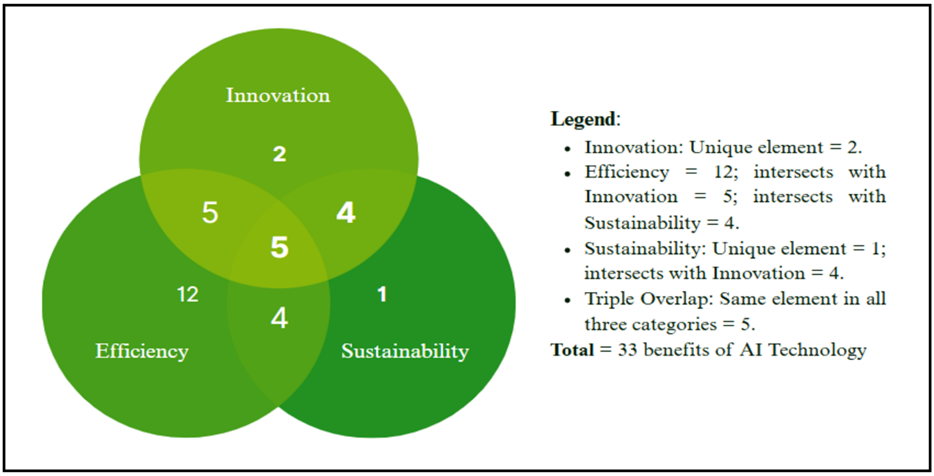

Fig. 5. Venn diagram of AI benefits in coffee agriculture: innovation, efficiency, and sustainability

The Venn diagram in Fig. 5 presents the distribution of AI's 33 benefits across three dimensions: Innovation, Efficiency, and Sustainability. It highlights unique contributions specific to each dimension and overlapping advantages shared across two or all three areas. Notably, while some AI applications clearly drive innovation or enhance sustainability, many generate synergies across multiple dimensions. For instance, five benefits are shared between Innovation and Efficiency, four between Innovation and Sustainability, and four between Efficiency and Sustainability. Importantly, five benefits impact all three dimensions, emphasizing AI's comprehensive potential to revolutionize coffee agriculture. Essentially, the diagram offers a succinct visual summary of AI's impact from multiple perspectives, helping to understand how AI can simultaneously drive innovation, improve efficiency, and support sustainable practices in the coffee industry.

The interaction between innovation, efficiency, and sustainability creates a synergy that reinforces the transformation of the coffee industry. For instance, AI-driven supply chain optimization – such as market demand forecasting by [80] – not only enhances operational efficiency but also reduces waste and supports long-term sustainability goals. Additionally, the development of AI-based coffee products, including smart sensors for aroma analysis [48] or automated roasting systems [44], exemplifies how technological innovation can increase economic value while minimizing environmental impact.

Table 3 outlines key research gaps and emerging opportunities in AI applications within coffee farming, accompanied by relevant research questions and the significance of addressing these areas for the future. Each research gap represents an unexplored domain where AI could make a substantial impact on the coffee industry.

Table 3. Future research directions in AI for coffee agriculture: gaps, questions, and importance

No	Research Gap and Novelty	Research Question (QR)	Importance for Future Research
1	Integration of AI with traditional farming practices for enhanced efficiency and sustainability	How can AI systems be integrated with traditional farming practices to improve efficiency and sustainability in coffee production?	Ensuring new technologies are widely adopted and support sustainability.
2	Long-term impact of AI on plant health and productivity	What are the long-term effects of AI technology on coffee plant health and plantation productivity?	Identifying potential risks and benefits for sustainable management strategies.
3	Development of more accurate predictive models for pest and disease management	How can we develop more accurate AI predictive models for coffee plant pest and disease management?	Improving efficiency and reducing chemical use for more environmentally friendly farming.
4	Water optimization through AI under climate change conditions	How can AI optimize water usage in coffee production amid climate change?	Supporting water resource sustainability and adaptation to climate change.
5	Personalizing consumer experiences through AI in the coffee industry	How can AI be used to personalize consumer experiences in the coffee industry and how does this influence brand loyalty?	Increasing customer satisfaction and competitive advantage in the coffee industry.
6	Enhancing collaboration among supply chain stakeholders using AI	How can AI improve collaboration and coordination among stakeholders in the coffee supply chain?	Promoting supply chain efficiency and shared value for all parties.

No	Research Gap and Novelty	Research Question (QR)	Importance for Future Research
7	Social and economic impact of AI implementation on small coffee farming communities	How does AI implementation affect the social and economic aspects of small coffee farming communities and how can challenges be addressed?	Ensuring equitable access to AI benefits and support community development.
8	Developing environmentally friendly AI systems using renewable energy	How can AI systems be developed to operate using renewable energy, making them more environmentally friendly?	Supporting the transition to a low-carbon economy and improving operational sustainability.
9	Role of AI in facilitating participatory and inclusive decision-making in coffee plantation management	How can AI facilitate participatory and inclusive decision-making in coffee plantation management?	Promoting fairer and more sustainable management practices that consider all stakeholders.
10	Evaluating costs and benefits of various AI applications in coffee production	How can the costs and benefits of various AI applications in coffee production be evaluated to ensure wise investments?	Assisting effective financial planning and AI technology investment decisions.

This table serves as a strategic roadmap for researchers and industry stakeholders, guiding them toward innovative, efficient, and sustainable solutions. By tackling these research questions, the coffee farming sector can fully harness AI's potential, ensure technological progress while promote environmental management and economic resilience. Moreover, Table 3 acts as a valuable resource, steering research efforts toward meaningful and impactful outcomes, fostering industry growth and resilience within an increasingly complex global landscape.

Table 3 identifies key research gaps and emerging opportunities in AI applications within coffee farming, outlining unexplored areas where AI can significantly impact the industry. Serving as a strategic roadmap for researchers and industry stakeholders, it guides efforts towards innovative, efficient, and sustainable solutions. Addressing these gaps will enable the sector to fully harness AI's potential, ensuring technological progress while simultaneously enhancing environmental management and economic resilience.

Future research should explore AI integration with traditional farming to optimize efficiency and sustainability, alongside long-term analyses on its impact on plant health and productivity. Developing more accurate predictive models for pest and disease management is crucial, as demonstrated by [42] on coffee leaf rust detection. Studies must assess AI's ecological influence, including risks such as pathogen resistance and biodiversity disruption, while considering its socioeconomic implications on smallholder farming communities and technology accessibility challenges, particularly with regulatory uncertainties and infrastructure limitations.

Further investigations should focus on AI-driven supply chain optimization, including real-time market demand forecasting and transparent tracking [80]. The development of affordable cloud-based platforms for SMEs could improve data analytics accessibility and automation, helping to overcome high investment costs. Moreover, AI-driven waste management innovations, such as organic waste conversion into bioenergy or compost [79], hold promise for sustainability. AI applications in personalized coffee experiences, including sensor systems for flavor analysis and robotic barista automation [38], could also enhance consumer interaction. Additionally, FlavourScape AI has demonstrated potential in standardizing brew quality [48], while AI-powered digital labelling could support consumer education on sustainability, showcasing carbon footprints and ethical sourcing [56].

3.1 Theoretical Implications

This study contributes to the understanding of digital transformation in the coffee industry, shaped by artificial intelligence (AI) across three key aspects: innovation, efficiency, and sustainability. AI-driven innovation has paved the way for new technological developments, such as real-time coffee bean quality monitoring, smart sensors for flavor analysis, and predictive algorithms for plant disease detection. Efficiency is enhanced through automation of production processes and resource optimization, while sustainability is reinforced by AI applications in coffee waste management and crop adaptation to climate change.

The interaction between these three aspects creates a digital synergy, reshaping the coffee industry's paradigm − where innovation drives efficiency, efficiency supports sustainability, and sustainability strengthens long-term competitiveness. Thus, this study enriches the literature on AI's role in agribusiness transformation while providing a theoretical foundation for further research on digital technology's impact on agriculture.

3.2 Practical Implications

The practical implications of this study highlight opportunities for AI implementation in the coffee industry to enhance productivity and sustainability holistically. AI-powered market demand prediction and supply chain transparency enable industry players to optimize distribution and reduce waste. Meanwhile, integrating AI into precision irrigation systems and coffee waste analysis helps farmers manage resources more efficiently and sustainably.

However, challenges such as high initial investment costs, dependence on digital infrastructure, and limited technological access for smallholder farmers need further attention. Future research must focus on developing inclusive and adaptive AI systems while exploring strategies to enhance technology adoption across different production scales. Here, AI is not only a tool for modernizing the coffee industry but also a catalyst for economic growth and agribusiness sustainability.

4 Conclusions and Future Research

The digital transformation of the coffee industry, driven by artificial intelligence (AI), has facilitated advancements in innovation, efficiency, and sustainability. AI-powered technologies, including real-time coffee bean quality monitoring, smart flavor analysis sensors, and computer vision-based classification, have significantly improved production standards. Additionally, AI has optimized supply chain management through market demand forecasting and automated processing, reducing operational costs and resource wastage. By integrating AI with blockchain, industry transparency has been enhanced, while precision irrigation systems and coffee waste repurposing into bioenergy demonstrate AI's contribution to environmental sustainability. The interplay between innovation, efficiency, and sustainability accelerates the modernization of the sector, establishing AI as a central force in shaping the future of agribusiness.

Future research should focus on enhancing AI's integration with traditional farming methods to boost productivity and long-term sustainability. Investigating AI's ecological impact, including pathogen resistance risks and biodiversity concerns, will be essential for sustainable implementation. Additionally, challenges such as high initial investment costs, limited technological accessibility for smallholder farmers, and regulatory instability must be addressed. Research opportunities exist in AI-driven supply chain optimization, the development of cloud-based platforms for SMEs, and innovations in coffee waste management technologies. With the right approach, AI will continue transforming the coffee industry, fostering a smarter, more efficient, and environmentally sustainable agribusiness landscape.

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