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AI-Driven Sustainability in the Restaurant Industry: A Review

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Abstract

Artificial intelligence (AI) is increasingly promoted as a means of advancing sustainability in the restaurant industry, yet systematic understanding of this intersection remains limited. The synthesis presented here rests on a small body of seven peer-reviewed empirical studies (2021–2025), and its conclusions should be read as preliminary indicators rather than as a settled body of knowledge. Three questions guide the synthesis: (1) which AI technologies are being applied to advance restaurant sustainability practices and which operational domains do they address; (2) what is the empirical evidence regarding the effectiveness of AI-driven interventions in reducing restaurant environmental impact; and (3) which organizational, technological, and contextual factors facilitate or impede successful AI adoption for restaurant sustainability purposes. Four AI technology categories emerged across the included studies: computer vision for food-waste monitoring, service robots, contact-free self-service systems, and blockchain–AI integration for supply-chain transparency. Reported effectiveness depends on the interplay between technology design, consumer psychology, and organizational readiness. The current evidence base is small, geographically concentrated, and methodologically heterogeneous; this review positions its findings as a preliminary framework to guide foodservice practitioners and to orient further empirical inquiry.

Keywords: artificial intelligence; restaurant sustainability; food-waste reduction; computer vision; technology adoption; circular economy

1. Introduction

The global restaurant industry stands at the intersection of two large pressures: rapid technological transformation and accelerating environmental accountability. Restaurants are resource-intensive operations, generating substantial impacts through food waste, energy use, water consumption, and supply-chain inefficiencies (Jia & Qiao, 2022; Renfors & Wendt, 2024). Food systems as a whole are responsible for roughly one third of global anthropogenic greenhouse-gas emissions (Crippa et al., 2021), and the foodservice sector contributes disproportionately to that total: commercial kitchens have been estimated to carry per-area carbon footprints two to five times greater than those of other commercial spaces (Sernizon Guimarães et al., 2024). At the same time, the industry continues to navigate the structural aftershocks of the COVID-19 pandemic—labor shortages, rising costs, and contactless and digital service models—that reshaped operations between 2020 and 2024 (Băltescu & Neacșu, 2022; Song et al., 2021). Within this landscape, artificial intelligence (AI) has begun to be positioned not as a peripheral add-on but as a potential mechanism for reconciling operational efficiency with sustainability goals (Huang et al., 2022; Mavani et al., 2022).

The economic importance of the restaurant industry compounds the urgency of this question. Restaurants are a primary employer in most economies, particularly for entry-level workers, and they shape dietary habits and community life (Kim & Jang, 2020). They also operate on thin margins (Yost et al., 2020), so the case for any new technology must rest on a clear link between adoption and measurable environmental or financial gains. Existing research demonstrates that restaurant characteristics—size, ownership structure, and market segment—significantly influence sustainability performance (Jang & Zheng, 2020), and that consumer awareness of environmental impact has risen sufficiently to reward sustainable practice and penalize visible negligence (Bouzari et al., 2022; Liu et al., 2020).

Corporate social responsibility (CSR), once peripheral, has become a strategic consideration for restaurant operators. CSR initiatives enhance customer satisfaction, brand loyalty, and employee retention (Guzzo et al., 2020; Lee et al., 2020; Sung & Lee, 2023), and CSR research in hospitality continues to expand (Peng et al., 2023). Yet implementation remains uneven, constrained by resource limitations, knowledge gaps, and the recurring tension between short-term profitability and long-term environmental investment (Wabanhu et al., 2025). It is in this implementation gap that AI is most often positioned as a productive intervention point.

AI applications in foodservice have proliferated rapidly. Documented use cases include demand forecasting, inventory optimization, personalized customer experiences, and operational automation (Lee et al., 2024; Parvez et al., 2025; Song et al., 2025). The technical foundations of these applications draw on continued advances in machine learning, deep learning, and natural-language processing (Cambria & White, 2014; Janiesch et al., 2021). Immersive technologies—virtual reality (VR), augmented reality (AR), and mixed reality (MR)—are increasingly integrated with AI in dining contexts as well, with implications for both customer experience and sustainability that are only beginning to be examined empirically (Cosio et al., 2023; Narayanan et al., 2024). The integration of all these technologies with explicit sustainability objectives, however, remains underexplored, and it is this intersection that the present review examines.

This article reviews the small but emerging body of peer-reviewed empirical work at the intersection of AI technologies and sustainability practices in the restaurant industry. The review is framed as a structured narrative review rather than a systematic review, in recognition of the limited empirical evidence currently available (Paul & Criado, 2020; Snyder, 2019). The remainder of the article is organized as follows: Section 2 sets out the conceptual landscape; Section 3 describes the review methodology, including a reproducible search protocol and quality appraisal; Section 4 presents the

synthesis organized around three guiding questions; and Section 5 discusses theoretical and practical implications, limitations, and future research directions.

2. Conceptual background

2.1 The operating environment of restaurants

Restaurants operate within an ecosystem characterized by thin margins, intense competition, and rapidly shifting consumer preferences. Compensation strategies materially affect firm performance (Kim & Jang, 2020), a balance between labor cost and service quality that shapes decisions across all operational domains, including sustainability investments. The COVID-19 pandemic accelerated trends toward contactless service, digital ordering, and delivery-centric models (Băltescu & Neacșu, 2022; Song et al., 2021), and altered consumer expectations such that health and safety concerns now intersect with sustainability considerations (Ryu et al., 2022).

Strategic differentiation has become a critical success factor in this environment. Deviation from industry norms can amplify both extremeness and volatility in firm outcomes (Park et al., 2023), with direct implications for sustainability positioning: restaurants that differentiate through environmental leadership may experience amplified performance effects, both positive and negative. Leadership characteristics, including CEO celebrity status, can moderate the relationship between environmental, social, and governance performance and operational outcomes (Nguyen et al., 2026). Institutional investors are an additional force shaping sustainability practice: institutional ownership is associated with stronger CSR–financial-performance linkages, and investor pressure can transform CSR from a moral imperative to an economic necessity (Yeon et al., 2025; Yost et al., 2020; Yu & Song, 2024).

2.2 Sustainability practices in restaurant operations

Sustainability in the restaurant industry is a multidimensional construct encompassing environmental stewardship, social responsibility, and economic viability. Empirical evidence shows that sustainable food practices positively influence operational outcomes (Abdou et al., 2023). Restaurant

characteristics—size, ownership, and market segment—significantly predict environmental performance (Jang & Zheng, 2020). At the high end of the market, Michelin-starred restaurants promote locality and sustainability simultaneously (Huang & Hall, 2023), and Michelin Green Star establishments demonstrate that comprehensive sustainability practice and culinary excellence are compatible (Biloslavo & Janković, 2025).

Food waste is the most pressing sustainability challenge in the sector. Recent bibliometric and review work identifies behavioral management and quantification as principal intervention points (Jia & Qiao, 2022; Sernizon Guimarães et al., 2024). Qualitative investigation reveals significant differences between front-of-house and back-of-house perspectives on waste mitigation (O'Neill et al., 2024), and managerial attitudes shape both barriers and enablers (Stirnimann & Zizka, 2022). Consumer behavior is also pivotal: self-efficacy and collective efficacy influence customer waste-reduction intentions through ethical judgment (Ding, 2022), and habit and emotion shape consumer waste-reduction behavior as predicted by the theory of interpersonal behavior (Mumtaz et al., 2022). Together, these findings indicate that effective waste reduction requires coordinated cognitive, emotional, and habitual interventions.

Green supply-chain management is increasingly central. Supplier-implemented practices drive environmental growth among small and medium-sized operations (Shin & Cho, 2022), and customer green interest moderates the relationship between regulatory frameworks and supply-chain practice (Wabanhu et al., 2025). Employee engagement is a critical enabler: customer pressure and ethical standards influence employee green behavior through green passion (Cho & Yoo, 2021), environmental awareness shapes workplace outcomes (Bouzari et al., 2022), and ethical climate supports work–family enrichment in restaurants (Lim et al., 2023). Brand positioning around sustainability has become more sophisticated, with brand attitude mediating environmental positioning effects (Liu et al., 2020), and interactive CSR campaigns shaping symbolic benefits through brand trust (Sung & Lee, 2023). National

health and environmental context also affects restaurant reputation (Fernández-Gámez et al., 2020). The circular economy provides a comprehensive frame for restaurant sustainability: case work documents the operational innovations required to operate “without bins” (Renfors & Wendt, 2024), and manager perspectives on food-waste separation are jointly shaped by institutional and internal pressures (Ng & Sia, 2023).

2.3 Restaurant corporate social responsibility

CSR research in restaurants has progressed from theoretical advocacy to strategic imperative. Systematic review work identifies gaps in understanding how CSR manifests at the individual and organizational levels (Guzzo et al., 2020), and bibliometric mapping documents emerging themes (Peng et al., 2023). CSR functions as a customer-satisfaction and retention strategy in chain restaurants (Lee et al., 2020), and CEO human-capital background (generalist vs. specialist) influences CSR strategy formulation (Park et al., 2024).

2.4 Artificial intelligence in restaurant operations

AI technologies now reach virtually every aspect of restaurant operations, from customer-facing interactions to back-of-house processes. A comprehensive assessment framework grounds the evaluation of AI in hospitality and tourism (Huang et al., 2022), recent evidence indicates significant productivity gains from digital transformation in restaurants (Lee et al., 2024), and the technical foundations draw from advances in machine learning and deep learning (Janiesch et al., 2021) and natural-language processing (Cambria & White, 2014). This section organizes the scholarly literature by AI application area, moving from sustainability planning through operational domains to service delivery and workforce development. Table 1 summarizes potential applications across ten operational areas and records the state of the peer-reviewed evidence in each. The survey is deliberately broader than the formal synthesis: it includes areas in which AI holds documented promise but no restaurant-specific

empirical study at the AI–sustainability intersection yet exists, whereas the typology in Section 4.1 is restricted to the seven studies meeting the inclusion criteria.

[Insert Table 1. Potential applications of AI across restaurant sustainability domains.]

Sustainability planning and integrated performance management form the strategic layer of AI application. Assessment frameworks support the evaluation of AI initiatives against organizational goals (Huang et al., 2022), interview evidence from hospitality professionals identifies AI-supported sustainability strategy as an emerging management practice (Filimonau et al., 2025), and qualitative case work documents how chain restaurants embedded digital transformation in post-pandemic strategy (Fainshtein et al., 2023). Restaurant-specific quantitative evidence at this strategic level has not yet been published.

Food-waste management is the application area with the deepest evidence base and anchors the synthesis in Section 4. Computer-vision systems weigh and classify kitchen waste in real time (Sigala et al., 2025), commercial platforms have been benchmarked against implementation criteria (Cejas, 2025), blockchain–AI architectures target waste across the supply chain (Omar et al., 2024), and review evidence documents AI's expanding role in food-waste reduction across hospitality (Vukolić et al., 2025).

Inventory control and demand forecasting are adjacent applications in which AI's sustainability contribution is plausible but, to date, efficiency-framed. Implementation guidance identifies machine-learning stock optimization and spoilage prediction as mature techniques (Mavani et al., 2022), reviews of food-industry automation document forecasting applications (Song et al., 2025), and digital transformation raises restaurant productivity more broadly (Lee et al., 2024). Studies connecting these capabilities to measured waste or resource outcomes in restaurants remain to be conducted.

Menu engineering and personalization link AI to consumption-side sustainability. Attractive AI avatars can nudge customers toward healthier choices (Hao et al., 2024), AI-enabled pricing on online platforms can align economic incentives with environmental goals when customer green awareness and

restaurant green effort are considered together (Zhang et al., 2025), and AI-driven menu recommendation has been prototyped within immersive ordering systems (Narayanan et al., 2024).

Energy management is among the least examined areas despite the sector's disproportionate energy intensity noted in the introduction. Interview evidence indicates that hospitality professionals view AI-driven optimization of energy and water use as a priority application (Filimonau et al., 2025), and survey evidence from hotels links integrated AI and IoT adoption to operational efficiency and sustainability outcomes (Gligorijević, 2024). No peer-reviewed study has yet examined AI-based energy optimization in restaurant settings specifically.

Supply-chain management and procurement extend AI's reach upstream of the kitchen. Blockchain–AI integration can support traceability and sustainability-claim verification (Omar et al., 2024), and AI applications in food processing, including meat processing and processing automation, identify waste-reduction opportunities that flow into restaurant supply chains (Jadhav et al., 2024; Wang & Li, 2024). AI-supported procurement decisions in restaurants have not yet been studied directly.

Customer service and AI-mediated service delivery have generated the most sustained research interest. Studies examine customer acceptance of AI-powered robot chefs in casual dining (Parvez et al., 2025), the role of anthropomorphic design, including humanoid robotic hands, in shaping food-quality perception (Zhu & Chang, 2020), segment-dependent acceptance patterns in fine versus casual dining (Nozawa et al., 2022), and the moderating role of server type in brand evaluation (Hwang et al., 2022).

Ordering systems and contact-free service carry direct sustainability implications through order accuracy and reduced material inputs. Contact-free service value influences the personal and social norms that shape sustainable behavioral intentions (Jang & Lee, 2021), quality-function-deployment methods inform kiosk design features that enhance customer experience while potentially reducing waste (Park et al., 2021), foundational service-operation frameworks continue to inform AI integration

in service delivery (Sampson, 2012), and immersive AI-based ordering prototypes aim to replace printed menus (Narayanan et al., 2024).

Employee training and workforce development complete the map. Systematic review evidence documents how AI reshapes hospitality employees' roles and required skills (Kumawat et al., 2025), and AI avatars are being piloted for scalable, personalized hospitality training (Sanders et al., 2025). In a sector with persistently high turnover and recurring training demands (Reynolds & Dolasinski, 2019), AI-supported training is a plausible but untested lever for embedding sustainability practice in daily operations.

Adjacent to these AI applications, immersive technologies—VR, AR, and MR—are increasingly proposed as complements to AI for sustainability communication and behavior change in dining contexts. A systematic review of XR for environmental sustainability identifies a growing but still-emerging literature on immersive technologies as tools for environmental learning, self-efficacy building, and behavior modification, while noting that empirical evidence of environmental impact remains limited (Cosio et al., 2023). In the restaurant setting specifically, Narayanan et al. (2024) describe a holographic VR-based ordering system integrated with AI-driven menu recommendation that aims to reduce paper waste by replacing printed menus, improve order accuracy through direct customer-to-kitchen transmission, and store transaction data on cloud-based infrastructure. The sustainability case in that work rests largely on input substitution (paper menus, manual ordering) rather than measured environmental outcomes, illustrating the gap between technical proof-of-concept and rigorous effectiveness evaluation that characterizes the broader literature.

3. Methodology

Given the small and heterogeneous body of empirical work currently available at the intersection of AI and restaurant sustainability, a structured narrative review was judged more appropriate than a systematic review (Paul & Criado, 2020; Snyder, 2019). Reproducibility, transparency,

and rigor were nonetheless prioritized through a documented search protocol, explicit inclusion and exclusion criteria, and a quality appraisal of included studies, all of which are described below.

3.1 Guiding questions

Three questions, derived from gaps identified in the conceptual background, guide the review:

RQ1. Which AI technologies are currently being applied to advance sustainability practices in the restaurant industry, and which operational domains do they address?

RQ2. What is the empirical evidence regarding the effectiveness of AI-driven interventions in reducing environmental impact and improving sustainability outcomes in restaurant operations?

RQ3. Which organizational, technological, and contextual factors facilitate or impede the successful adoption of AI for sustainability purposes in restaurant settings?

3.2 Search protocol

Three databases were searched: Scopus, Web of Science (Core Collection), and Google Scholar. The principal search was conducted between January 15 and February 28, 2025, with the final search update extended to December 31, 2025; a sensitivity search conducted in January 2026 confirmed that no additional eligible records were missed. In Scopus, the search was applied to title, abstract, and keywords. In Web of Science, the search was applied to the topic (TS) field. Google Scholar was used for complementary searching of citations and forward/backward chaining. The Boolean strings executed against each database are reported in Table 2.

[Insert Table 2. Search strings executed in each database.]

3.3 Inclusion and exclusion criteria

Records were included if they (i) were full peer-reviewed journal articles, (ii) were published in English between January 1, 2021 and December 31, 2025, (iii) reported empirical or conceptual analysis at the intersection of AI applications and restaurant sustainability practices, and (iv) included sufficient detail on the AI application and the sustainability outcome to support synthesis against the three

research questions. Records were excluded if they (i) were non-peer-reviewed (books, book chapters, conference proceedings, theses, gray literature), (ii) were not available in English, (iii) addressed AI in foodservice contexts without reference to sustainability outcomes, or (iv) addressed sustainability in restaurants without reference to AI-enabled interventions.

Whether a study sufficiently connected AI with sustainability outcomes was judged with a two-part rule at full-text review. A record was retained when (a) an AI-enabled system, defined here as machine learning, computer vision, natural-language processing, service robotics, or AI-integrated blockchain, was a focal object of the investigation rather than incidental context, and (b) at least one sustainability construct, such as food-waste mass, resource or energy use, sustainable behavioral intention, or supply-chain sustainability verification, was measured, modeled, or formally theorized as an outcome of that system. Both conditions had to hold. The 24 full-text records excluded for insufficient integration typically failed one of them, most often by invoking sustainability only as motivation in the framing or by examining AI adoption without a sustainability construct in the design.

3.4 Screening and data extraction

A total of 629 records were identified through database searching (Scopus n = 342; Web of Science n = 198; Google Scholar supplementary search n = 89). After removing 58 duplicates, 571 titles and abstracts were screened against the inclusion and exclusion criteria. Of these, 520 were excluded as off-topic at the title and abstract level. Full-text review of the remaining 51 articles led to exclusion of 43 records (insufficient AI–sustainability integration n = 24; lack of empirical content n = 12; methodological concerns n = 7), leaving 7 articles for inclusion in the synthesis. Screening was conducted by the first author; 20 percent of records (n = 114) were double-screened by a second reviewer with inter-rater agreement of Cohen's $\kappa = 0.83$, indicating strong concordance, and disagreements were resolved by discussion. Each included study was coded for (a) AI technology and operational domain (RQ1), (b) reported sustainability outcomes and effectiveness measures (RQ2), and (c) facilitating and impeding

factors (RQ3), following the data-extraction approach described by Snyder (2019) and the qualitative content-analysis approach of Hsieh and Shannon (2005).

3.5 Quality appraisal of included studies

A streamlined quality appraisal was performed against five criteria adapted from the Mixed Methods Appraisal Tool (Hong et al., 2018): clarity of research question and study design; appropriateness of sampling or case selection; rigor of data collection; transparency of analysis; and adequacy of interpretation in relation to reported evidence. Each study was rated as Strong, Adequate, or Limited on each criterion (Table 3). The small sample size, the absence of randomized or controlled designs, and the geographic concentration of studies are noted as collective limitations of the evidence base and are returned to in Section 5.4. Criterion definitions and the rating anchors used for these judgments are provided in Appendix A.

[Insert Table 3. Quality appraisal of included studies (n = 7).]

4. Findings

The review identified seven peer-reviewed studies examining AI and sustainability in restaurant operations (Table 4). The included studies are marked with an asterisk throughout this section to distinguish them from background references. The seven studies employed structural equation modeling on survey data (Jang & Lee, 2021; Parvez et al., 2025), multi-site quasi-experimental field intervention with quantitative effectiveness measurement (Sigala et al., 2025), multi-criteria decision analysis (Cejas, 2025), qualitative case work on post-COVID digital transformation (Fainshtein et al., 2023), conceptual–technical analysis of blockchain–AI integration (Omar et al., 2024), and a comparative customer-response study across dining segments (Nozawa et al., 2022). Geographic coverage included Europe, the Asia-Pacific region, North America, and parts of Eastern Europe, with publication dates from 2021 to 2025.

[Insert Table 4. Characteristics of included studies (n = 7).]

4.1 RQ1: AI technologies and operational domains

The technology typology presented in this section was derived inductively from the seven included studies and therefore reflects only those AI applications for which peer-reviewed empirical evidence explicitly framed as AI-and-sustainability is currently available. Adjacent applications discussed in the conceptual background—notably AI-driven demand forecasting and menu engineering—are real and growing in industry practice but have not yet been the subject of empirical study explicitly framed at the AI–sustainability intersection; they are therefore noted as contextual but excluded from the formal typology. Immersive technologies (VR/AR/MR) similarly appear in adjacent conceptual or proof-of-concept work (Cosio et al., 2023; Narayanan et al., 2024) but were not represented among peer-reviewed empirical studies meeting the inclusion criteria for this review.

With those scope conditions stated, the seven included studies span four distinct categories of AI technology, each addressing specific operational challenges. Computer-vision systems for food-waste monitoring were the most extensively documented technology. Sigala et al. (2025) deployed a fully automatic, AI-based waste-tracking system using computer vision and deep learning to weigh and optically segregate food waste in real time across five HORECA establishments. Pre-intervention baseline measurements (recorded over a 2–4 week period at each site) ranged from 76.2 to 151.9 grams of food waste per meal served, with avoidable waste constituting 45–73 percent of that baseline mass. Cejas (2025) benchmarked four platforms (Winnow Vision, Leanpath, Kitro, and Too Good To Go) against criteria including waste-reduction capability, implementation cost, data accuracy, and integration time. Together, these two studies establish computer vision as the dominant AI application in this evidence base for sustainability purposes.

Service robots and AI-mediated customer service constitute a second category. Parvez et al. (2025) documented motivational drivers (functionality and hedonic/cognitive innovativeness) that influence customer acceptance of AI-powered robot chefs in casual-dining settings. Nozawa et al. (2022)

showed that customer response to AI varies sharply across dining segments, with luxury contexts generating more negative reactions than casual dining contexts. Contact-free and self-service AI systems form a third category: Jang and Lee (2021) demonstrated that contact-free service value influences personal and social norms, which in turn shape sustainable behavioral intentions. Blockchain–AI integration forms the fourth category: Omar et al. (2024) proposed an architecture combining blockchain's tamper-evident record-keeping with AI's analytical capacity to create traceable supply chains for sustainability-claim verification and food-waste reduction in hospitality. Fainshtein et al. (2023) contextualize these technologies within the post-COVID innovation landscape of chain restaurants.

Across these four categories, food-waste management is the dominant operational domain in the present evidence base, addressed by five of the seven included studies. Secondary domains included customer-service delivery, menu and ordering optimization, decision support, and supply-chain transparency.

4.2 RQ2: Effectiveness of AI-driven interventions

The evidence base reveals a complex picture in which effectiveness depends on technology type, implementation context, and outcome measure. Quantitative work provides statistical support for AI's influence on sustainability-related behaviors and outcomes. Jang and Lee (2021) demonstrated that contact-free service value significantly influences personal norms ($\beta = 0.198$, $p < .001$), which in turn affect sustainable behavioral intentions. Social norms exerted a stronger influence than personal norms in that model, suggesting that AI systems designed to draw on collective behavior may achieve greater sustainability impact than systems targeting individual attitudes alone.

For food-waste monitoring, the multi-site field intervention by Sigala et al. (2025) documented reductions of up to 51 percent in total food waste by mass (grams per meal served) against pre-intervention baselines at the five participating HORECA sites, with corresponding cost savings. Cejas

(2025) generated comparative effectiveness rankings across the four major platforms based on weighted criteria; respondents in that study reported, on a Likert scale, that AI implementation improved order-processing time by approximately 53 percent (self-reported relative improvement) and that 50 percent of participating restaurants experienced reductions in food waste, though the survey design did not include direct measurement of waste mass. These findings warrant careful interpretation: they are derived from specific operational contexts and weighting choices, and Cejas's (2025) percentages reflect respondent perceptions rather than measured outcomes.

Qualitative evidence complements these quantitative findings. Sigala et al. (2025) observed that the data-driven intervention raised staff awareness toward food waste, facilitating behavioral changes that complement the technological component. Fainshtein et al. (2023) documented how chain restaurants with sufficient resources to develop technological solutions and build customer loyalty were more resistant to pandemic-era disruption. Significant evidence gaps remain: longitudinal effectiveness data, experimental designs with control conditions, and standardized sustainability metrics are all scarce. Omar et al. (2024) explicitly noted that "there remains a distinct lack of research addressing the challenges associated with managing food waste during the consumption phase," and Sigala et al. (2025) similarly emphasized the dearth of evidence-based information on the effectiveness, transferability, and long-term sustainability of AI-based interventions.

4.3 RQ3: Facilitators and barriers to AI adoption

The Technology–Organization–Environment (TOE) framework (Tornatzky & Fleischer, 1990) provides the principal organizing structure for the findings on adoption factors. TOE identifies three dimensions that jointly shape technology adoption decisions: the technological context (characteristics of the technology and its compatibility with existing systems), the organizational context (firm structure, leadership, employee readiness, resource availability), and the environmental context (regulatory pressure, competitive dynamics, market characteristics). Recent application of TOE to AI adoption in

hospitality (Filimonau et al., 2025) supports its use as an organizing frame for the evidence synthesized here.

Across the seven included studies, successful AI–sustainability implementation depends on alignment across all three TOE dimensions. Organizational facilitators include leadership commitment, chain-restaurant infrastructure providing data availability across locations, and employee engagement supported by ethical organizational climate (Cho & Yoo, 2021; Fainshtein et al., 2023; Lim et al., 2023). Chain restaurants enjoy structural advantages from standardized processes, centralized decision-making, and economies of scale (Fainshtein et al., 2023). Technological facilitators include cloud-based infrastructure that integrates with existing workflows and data accuracy that supports user trust (Narayanan et al., 2024). Cejas (2025) emphasized that lower deviation between expected and observed performance reflects smoother integration with existing systems. Contextual facilitators include external funding support (Sigala et al., 2025), regulatory frameworks that encourage sustainability measurement, and customer acceptance of AI-mediated service in appropriate segments (Nozawa et al., 2022).

Barriers span multiple dimensions. Financial constraints are the most frequently cited obstacle: high initial capital, ongoing maintenance costs, and uncertain return-on-investment timelines prove prohibitive for smaller operations (Song et al., 2025; Vukolić et al., 2025). Data-quality challenges compound these difficulties because AI and machine-learning effectiveness depends fundamentally on the quality and volume of training data (Song et al., 2025). Consumer-acceptance challenges vary by dining context: Nozawa et al. (2022) documented distinct acceptance patterns across restaurant segments, with customers reacting negatively to AI in contexts where the human touch is highly valued, particularly in emotion-oriented luxury fine dining.

5. Discussion

The synthesis of seven peer-reviewed studies should be read as a preliminary indicator of AI's sustainability potential in restaurants rather than as a settled body of knowledge. The limited corpus

reflects the nascent state of empirical work at the AI–sustainability intersection (Munn et al., 2018), and the findings below are framed accordingly.

5.1 Theoretical implications

The review surfaces three theoretical contributions. First, the demonstration that contact-free service value influences personal and social norms, which in turn shape sustainable behavioral intentions (Jang & Lee, 2021), suggests that AI systems can serve as norm-activation mechanisms that trigger psychological processes promoting sustainability. This finding extends the Norm Activation Model (Schwartz, 1977) into AI-mediated service contexts, and indicates that the activation pathway operates not only through cognitive deliberation but also through structural features of the service interface itself. The stronger influence of social norms in Jang and Lee's (2021) model has implications for AI design: systems that draw on social proof and collective behavior may achieve greater sustainability impact than systems that target individual attitudes alone.

Second, the review highlights the complex, non-linear relationship between anthropomorphic design and technology acceptance. Robot attributes such as anthropomorphism, likeability, perceived intelligence, and perceived safety influence customer response (Parvez et al., 2025; Zhu & Chang, 2020), but customers do not necessarily prefer maximum human-likeness (Zhu & Chang, 2020). Attractive avatars can promote healthier dining choices (Hao et al., 2024), suggesting AI-mediated interactions can influence consumption behavior in sustainability-relevant ways.

Third, the review extends rather than merely confirms the TOE framework (Tornatzky & Fleischer, 1990). The included evidence suggests that two environmental-context factors deserve explicit treatment in TOE applications to AI–sustainability in restaurants: regulatory pressure on food waste (notably the EU Horizon 2020 sustainability funding that enabled the Sigala et al. (2025) intervention) and customer green awareness (which functioned as a moderator in several included studies). These factors are not foregrounded in the original TOE formulation but appear repeatedly in

the AI–sustainability evidence base, suggesting that a TOE+E (environment-extended) variant may be more suitable for this domain.

5.2 Practical implications for foodservice operators

Three practical implications follow, each appropriately scoped to the small evidence base. First, on technology selection: Cejas (2025) offers a useful decision-making structure for restaurant operators with specific operational priorities, although replication across diverse settings is required before the precise rankings should be treated as a benchmark. Operators should assess their primary sustainability challenges and select AI solutions aligned with those priorities. Mavani et al. (2022) provide complementary implementation guidance on technical requirements.

Second, on human–AI collaboration design: acceptance of AI depends on contextual fit. Motivational drivers of innovativeness (Parvez et al., 2025), expectations across dining segments (Nozawa et al., 2022), and customer responses to AI's physical appearance and communication modes (Hao et al., 2024; Zhu & Chang, 2020) should inform deployment strategy. Jang and Lee (2021) recommend maintaining well-trained employees alongside contact-free systems to assist customers uncomfortable with technology-only interactions.

Third, on supply-chain integration: upstream AI applications in food processing offer waste-reduction opportunities that extend to restaurant supply chains (Jadhav et al., 2024; Wang & Li, 2024). Blockchain–AI integration can support transparency and accountability across supply chains and sustainability-claim verification (Omar et al., 2024). This implication rests on only one of the seven included studies (Omar et al., 2024) and should be treated as direction-setting rather than evidence-rich. The reported 51 percent food-waste reduction figure (Sigala et al., 2025) is promising but context-specific to the HORECA sites studied, and the statistical relationship between contact-free service value and personal norms (Jang & Lee, 2021) represents initial evidence requiring further validation across cultural and market contexts.

5.3 SME pathways and constraints

The unique challenges facing small and medium-sized enterprises (SMEs) warrant dedicated examination. The restaurant industry is predominantly composed of SMEs, yet most AI–sustainability solutions in the included studies were developed and tested in chain-restaurant contexts characterized by standardized processes and economies of scale (Fainshtein et al., 2023). Financial barriers are the most significant impediment to AI adoption among restaurant SMEs (Eze et al., 2024; Ferraris et al., 2021). Unlike large organizations, SMEs typically operate with constrained budgets and limited access to capital, making large technology investments prohibitively risky. The AI platforms documented in this review require initial capital expenditure for hardware, software licensing, and integration that may exceed the investment capacity of independent operators, and ongoing expenses for maintenance, updates, and training compound the burden. Return-on-investment timelines for AI–sustainability technologies may extend beyond acceptable payback periods for thin-margin operations, particularly where benefits accrue gradually through waste reduction. Access to external funding mechanisms is also unequal: while the Sigala et al. (2025) study benefited from EU Horizon 2020 support, most independent operators lack the administrative capacity to identify and manage research-grant opportunities.

Beyond finance, SMEs face barriers related to technical expertise and human capital (Eze et al., 2024). AI and machine-learning effectiveness depends on data quality and volume (Song et al., 2025), and smaller operations generate less transactional data and often lack systematic data-collection practices. Without dedicated IT personnel, SMEs struggle to implement, calibrate, and maintain AI systems that require ongoing technical attention. The computer-vision systems documented by Sigala et al. (2025) presuppose technical infrastructure and expertise that independent restaurants typically cannot sustain. Staff training is an additional human-capital challenge in a sector with high turnover (Reynolds & Dolasinski, 2019). Organizational culture in SMEs can also resist technological change. Owner-operators who have built successful businesses through traditional methods may perceive AI as

unnecessary disruption to established routines (Ferraris et al., 2021). Consumer-acceptance findings carry differential implications: many SMEs operate in neighborhood or community-oriented segments where personal relationships and human service are central to the value proposition, and AI adoption risks alienating customer bases that prize authentic interaction (Nozawa et al., 2022).

Despite these barriers, viable pathways exist for SMEs to participate in AI-driven sustainability. Cloud-based and software-as-a-service models convert capital expenditure to operational expenditure and may align better with SME cash-flow patterns; Narayanan et al. (2024) describe one such cloud-hosted architecture appropriate for smaller operators. Industry consortia and cooperative platforms could enable shared AI infrastructure across independent restaurants, allowing collective access to scale economies. Phased implementation—simple food-waste tracking, digital inventory management, and basic demand forecasting before more ambitious AI investments—establishes data-collection practices and demonstrates value before larger commitments. Government policy can address market failures through targeted subsidies, tax incentives, and technical-assistance programs, as the success of EU Horizon 2020 funding in supporting Sigala et al. (2025) illustrates. Finally, technology vendors bear responsibility for developing SME-appropriate offerings (simplified interfaces, reduced data requirements, flexible pricing, and integrated training) because the platforms currently dominating the market were designed for enterprise-scale operations.

5.4 Limitations

This review has several limitations. First, the small sample (n = 7) reflects the nascent state of empirical work at the AI–sustainability intersection rather than a deficiency of the review process, but it constrains the strength of the inferences that can be drawn (Haddaway et al., 2015). Second, the methodological heterogeneity of the included studies—spanning SEM surveys, multi-site field interventions, multi-criteria decision analysis, qualitative case studies, and design-science conceptual work—precludes formal quantitative synthesis even at a descriptive level. The seven studies use

different outcome measures (behavioral intentions, waste mass per meal, acceptance ratings, comparative platform rankings) and different time horizons, making cross-study effect aggregation inappropriate. Readers should therefore interpret the synthesis as a narrative integration of heterogeneous evidence rather than as the basis for pooled estimates.

Third, publication bias may skew the included studies toward successful AI implementations, since work documenting failures or negative outcomes is less likely to reach publication. Fourth, the rapid pace of technological evolution means findings may become outdated as new capabilities emerge. Fifth, geographic concentration is pronounced: three of the seven included studies were conducted in Europe (Germany, Switzerland, Greece, and Slovenia in the case of relevant background work), two in the Asia-Pacific region (South Korea, Asia-Pacific blockchain applications), and one each in North America (United States) and Eastern Europe (Ukraine/post-Soviet context). This concentration limits generalizability to contexts where restaurant operations, sustainability challenges, and technology infrastructure differ. The geographic distribution also suggests that AI–sustainability adoption may be moderated by regional regulatory environments; the EU Farm-to-Fork strategy and the broader EU Green Deal regulatory framework are unlikely to be matched by equivalent policy levers elsewhere, and this moderation deserves explicit empirical investigation.

Sixth, restricting inclusion to English-language publications introduces language bias. Several of the countries most active in restaurant technology, service robotics, and sustainability policy, among them Japan, South Korea, China, Germany, Switzerland, the Netherlands, and the Nordic countries, sustain research literatures in their own languages. Excluding that work may understate both the volume and the geographic diversity of the available evidence, and it compounds the geographic concentration described above. Reviews with multilingual search capacity should revisit this intersection as the literature grows.

5.5 Future research

Several productive directions follow from the evidence gaps identified above. Most pressing is the need for longitudinal designs that track sustainability outcomes over extended periods; current evidence relies predominantly on cross-sectional snapshots that cannot establish the durability of reported gains. Experimental work with appropriate control conditions would strengthen causal inference: reported reductions on the order of 30 to 51 percent in food waste are promising but require rigorous causal designs to be treated as benchmarks. The development of standardized sustainability metrics is a further priority. Three candidate frameworks deserve consideration: the United Nations SDG 12.3 monitoring framework, which defines the Food Loss Index and Food Waste Index with established measurement protocols; the IFRS Sustainability Disclosure Standards (S1 general requirements and S2 climate-related disclosures), which provide enterprise-level reporting consistency; and the SASB Food and Beverage Industries standards, which include sector-specific metrics on food waste, ingredient sourcing, and energy management.

Cross-regional comparative research is a further priority, given the geographic concentration of the current evidence base. Studies that compare AI–sustainability adoption across regulatory environments would clarify how environmental-context factors moderate effectiveness. Integration of emerging technologies (including large language models, edge computing, IoT-connected kitchen equipment, and AI–XR hybrid systems) with existing AI–sustainability applications warrants systematic investigation (Cosio et al., 2023). Comparative research across restaurant segments would also provide guidance for practitioners, given that AI acceptance and effectiveness vary substantially across quick-service and fine-dining establishments (Nozawa et al., 2022). Finally, rigorous economic analysis of AI investments, particularly for SMEs, would strengthen the business case for sustainability initiatives and address the financial barrier most frequently cited in the reviewed literature.

The gaps recorded in Table 1 define an agenda of their own. Seven of the ten operational areas in that table lack any restaurant-specific empirical study at the AI and sustainability intersection:

sustainability planning and integrated performance management, inventory control, demand forecasting, menu engineering, energy optimization, procurement, and employee training. Current evidence in these areas is efficiency-framed, hotel-based, or conceptual. Studies that measure sustainability outcomes directly in restaurant settings, for example energy use in smart kitchen operations, overproduction avoided through demand forecasting, or waste reduction attributable to AI-supported procurement, would convert documented potential into an evidence base.

6. Conclusion

The available evidence suggests that artificial intelligence may support sustainability gains in restaurant operations, but the evidence base is small, geographically concentrated, and methodologically heterogeneous, and definitive conclusions are not yet warranted. Across seven peer-reviewed empirical studies, four AI technology categories—computer-vision food-waste monitoring, service robots, contact-free self-service systems, and blockchain–AI supply-chain integration—emerge as the most studied applications. Reported effectiveness depends on the interplay between technology design, consumer psychology, and organizational readiness, and adoption hinges on alignment across technological, organizational, and environmental conditions consistent with an environment-extended TOE framework. The synthesis offered here should be read as a preliminary framework: it identifies promising directions for foodservice practice and orients future empirical work, but the small evidence base does not yet support definitive conclusions. Strengthening this evidence base—through longitudinal designs, controlled experimental work, standardized sustainability metrics aligned with established reporting frameworks (SDG 12.3, IFRS S1/S2, SASB), cross-regional comparative work, and SME-focused investigation—is the central agenda for the next several years of research at the AI–sustainability intersection in restaurants. The agenda also runs wider than the seven included studies. As Table 1 records, most of the operational areas in which AI could plausibly support restaurant sustainability, including AI-driven sustainability planning, predictive analytics for demand and

procurement, smart kitchen operations, energy optimization, employee training, and integrated sustainability performance management, have not yet been examined empirically. Until they are, the promise documented in this review remains a set of hypotheses for empirical work rather than an established result.

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Table 1. Potential applications of AI across restaurant sustainability domains.

Operational area	Example AI applications	Representative sources	Evidence status
Sustainability planning and integrated performance management	AI-supported sustainability strategy; assessment frameworks; digital-transformation strategy	Huang et al. (2022); Filimonau et al. (2025); Fainshtein et al. (2023)*	One included qualitative study at strategy level; otherwise conceptual and interview-based. Research gap.
Food-waste management	Computer-vision waste tracking; platform benchmarking; blockchain-AI waste reduction	Sigala et al. (2025)*; Cejas (2025)*; Omar et al. (2024)*; Vukolić et al. (2025)	Strongest area: three included studies plus adjacent review evidence.
Inventory control	Machine-learning stock optimization; spoilage prediction	Mavani et al. (2022); Song et al. (2025)	Adjacent guidance and review work; no restaurant sustainability study. Gap.
Demand forecasting	Predictive analytics reducing overproduction	Lee et al. (2024); Mavani et al. (2022)	Adjacent empirical work, productivity-framed. Gap at the sustainability intersection.
Menu engineering and personalization	AI menu recommendation; avatar-based nudging; AI-enabled pricing with green awareness	Hao et al. (2024); Zhang et al. (2025); Narayanan et al. (2024)	Adjacent empirical and proof-of-concept work. Gap.
Energy management	AI and AI-IoT optimization of kitchen and building energy use	Filimonau et al. (2025); Gligorijević (2024)	Adjacent empirical work, hospitality-wide or hotel-based; no restaurant-specific study. Gap.
Supply-chain management and procurement	Blockchain-AI traceability and sustainability-claim verification; AI in upstream food processing	Omar et al. (2024)*; Jadhav et al. (2024); Wang & Li (2024)	One included conceptual-technical study; adjacent upstream evidence. Gap on procurement decisions.
Customer service and AI-mediated service	Robot chefs; service robots; segment-dependent acceptance	Parvez et al. (2025)*; Nozawa et al. (2022)*; Zhu & Chang (2020); Hwang et al. (2022)	Two included empirical studies plus adjacent experimental work.
Ordering systems and contact-free service	Contact-free service value and norm activation; kiosk design; VR-AI ordering	Jang & Lee (2021)*; Park et al. (2021); Narayanan et al. (2024)	One included empirical study plus adjacent design work.
Employee training and workforce development	AI avatars for training; AI effects on employee skills and roles	Kumawat et al. (2025); Sanders et al. (2025)	Adjacent hospitality-wide evidence; no restaurant sustainability study. Gap.

Note. * indicates one of the seven studies included in the formal synthesis (Section 4 of the manuscript). Evidence status reflects peer-reviewed work available at the December 31, 2025 search cutoff.

Table 2. Search strings executed in each database.

Database	Search string (as executed)
Scopus (TITLE-ABS-KEY)	("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "computer vision" OR "natural language processing") AND ("restaurant*" OR "foodservice" OR "food service" OR "HORECA") AND ("sustainab*" OR "food waste" OR "green" OR "environment*" OR "circular econom*")
Web of Science (TS)	TS=(("artificial intelligence" OR "machine learning" OR "deep learning" OR "computer vision") AND ("restaurant" OR "foodservice" OR "HORECA") AND ("sustainability" OR "food waste" OR "green practice" OR "environmental impact"))
Google Scholar (complementary, citation chaining)	"AI" "restaurant" "sustainability"; "AI" "food waste" "restaurant"; "machine learning" "restaurant operations" "green"; "AI" "sustainable supply chain" "restaurant"; "AI" "restaurant management" "environmental impact"

Table 3. Quality appraisal of included studies (n = 7).

Study	Research question / design	Sampling / case selection	Data collection	Analysis transparency	Interpretation vs. evidence	Overall
Jang & Lee (2021)	Strong	Adequate	Adequate	Strong	Adequate	Adequate
Nozawa et al. (2022)	Strong	Strong	Strong	Strong	Adequate	Strong
Fainshtein et al. (2023)	Adequate	Adequate	Strong	Adequate	Limited	Adequate
Parvez et al. (2025)	Strong	Strong	Strong	Strong	Strong	Strong
Sigala et al. (2025)	Strong	Strong	Strong	Adequate	Strong	Strong
Omar et al. (2024)	Adequate	Adequate	Adequate	Adequate	Adequate	Adequate
Cejas (2025)	Adequate	Limited	Adequate	Adequate	Adequate	Adequate

Note. Criteria adapted from the Mixed Methods Appraisal Tool, version 2018 (Hong et al., 2018); criterion definitions and rating anchors appear in Appendix A of the manuscript. The overall rating is the modal (most frequent) rating across the five criteria.

Table 4. Characteristics of included studies (n = 7).

Study	Method	Setting / Sample	AI focus
Jang & Lee (2021)	Survey + SEM	n = 310 Korean restaurant customers	Contact-free self-service (effect on personal/social norms)
Nozawa et al. (2022)	Two experimental studies	Customer response in luxury vs non-luxury contexts	AI-mediated service across dining segments
Fainshtein et al. (2023)	Qualitative case study (interviews with 16 chain CEOs)	Post-COVID restaurant industry	Digital transformation including AI-enabled service
Parvez et al. (2025)	Survey + PLS-SEM	n = 489 casual-dining customers (Florida, USA)	AI-powered robot chefs (acceptance)
Sigala et al. (2025)	Multi-site quasi-experimental field intervention	5 HORECA establishments in Germany, Switzerland, Greece	AI-based computer-vision waste-tracking devices
Omar et al. (2024)	Design science / technical-conceptual analysis	Blockchain-AI architecture for hospitality food-waste tracking	Blockchain–AI integration for supply-chain transparency
Cejas (2025)	Multi-criteria decision analysis	Comparative evaluation of Winnow Vision, Leanpath, Kitro, Too Good To Go	AI food-waste platforms (effectiveness ranking)

Appendix A. Quality-appraisal criteria and rating anchors

The five criteria used in the quality appraisal (Section 3.5) were adapted from the Mixed Methods Appraisal Tool, version 2018 (Hong et al., 2018). Table A1 defines each criterion, and Table A2 defines the rating levels applied to each criterion. Because the included studies span quantitative, qualitative, and design-science traditions, each criterion was applied within the study's own methodological tradition, following the design-specific logic of the MMAT. The overall rating reported in Table 3 is the modal (most frequent) rating across the five criteria. Ratings were assigned by the author.

Table A1. Quality-appraisal criteria.

Criterion	**Definition**
Clarity of research question and study design	The study states its question or objective, and the chosen design is capable of answering it.
Appropriateness of sampling or case selection	Participants, sites, or cases suit the question, and their selection is described and justified.
Rigor of data collection	Instruments, procedures, and measures are reported and fit for purpose.
Transparency of analysis	Analytic procedures are reported in enough detail to be followed and, in principle, repeated.
Adequacy of interpretation	Conclusions follow from the reported evidence and stay within it.

Table A2. Rating levels and anchors.

Rating	**Anchor**
Strong	The element is explicitly reported and fully appropriate to the study aim, with enough detail for independent judgment.
Adequate	The element is reported and broadly appropriate, with minor omissions that do not threaten the credibility of the findings.
Limited	The element is missing, partially reported, or raises concerns that materially qualify the findings.