Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 8, 1002-1013
2025
Publisher: Learning Gate
DOI: 10.55214/2576-8484.v9i8.9526

Artificial intelligence in restaurants: A solution to forecast demand and reduce food waste in Miraflores

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Abstract: This investigation assessed the impact of an artificial intelligence (AI)-powered demand prediction system on minimizing food waste in medium-scale restaurants located in Miraflores, Lima, Peru. Employing a quantitative pre-experimental approach with baseline and follow-up assessments, the study evaluated operational metrics from five establishments over a six-week period. The AI system, developed using machine learning techniques such as Random Forest and Gradient Boosting, generated daily projections of ingredient requirements by leveraging historical transaction records and situational factors. The findings revealed a significant reduction in daily food waste, decreasing from 4.12 kg to 2.76 kg after implementation. Statistical analyses indicated strong internal consistency ($\alpha = 0.841$), normally distributed data, and a statistically significant difference in means ($p < 0.001$). These results highlight the value of AI-enhanced decision-making in optimizing resource use, reducing operational costs, and promoting sustainable practices within the food service industry. The study provides valuable empirical insights into digital innovation in hospitality, particularly relevant to the Latin American region.

Keywords: *Food service industry, Machine learning, Operational, Smart operations, Sustainability.*

1. Introduction

The quest for operational effectiveness and environmental sustainability represents a critical issue within the food service sector, particularly in bustling urban areas where tourism converges with local dining traditions. In Miraflores, a dynamic culinary center in Lima, Peru, restaurants face ongoing demands to streamline processes, align supply with demand, and curb food waste. Despite their efforts, many establishments continue to depend on conventional, intuition-driven approaches for anticipating daily demand, which frequently leads to excess food, elevated expenses, and adverse environmental consequences.

Globally, food waste has become a major concern for sustainability. The Food and Agriculture Organization (FAO) estimates that nearly one-third of the food produced globally is wasted, equating to approximately 1.3 billion tons per year. This has far-reaching consequences, not only in terms of lost economic value and inefficient use of resources, but also due to its contribution to climate change through methane emissions from decomposing organic waste. Restaurants and food service establishments are key contributors to this problem, often due to limited forecasting capabilities, over-preparation, and lack of real-time inventory data.

Food waste extends beyond mere logistical challenges, impacting profitability, complicating kitchen operations, and exacerbating broader sustainability concerns. This raises a pivotal question: How can restaurants in vibrant urban settings leverage real-time, data-informed strategies to better match food production with actual consumption? In response, emerging digital technologies offer novel solutions that can shift traditional business models toward smarter, more sustainable operations.

Recent progress in Artificial Intelligence (AI) offers promising avenues to tackle this issue. Research has shown AI's capacity to improve essential aspects of restaurant management, such as demand

History: Received: 16 June 2025; Revised: 5 August 2025; Accepted: 8 August 2025; Published: 19 August 2025
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forecasting, tailored customer interactions, workforce coordination, and inventory oversight [1, 2]. AI-based systems, particularly those built on machine learning algorithms, are capable of analyzing vast datasets encompassing transaction history, customer behavior, external factors like weather and holidays—to generate accurate forecasts and inform decision-making [3, 4]. These tools not only enhance accuracy but also help reduce subjectivity and dependence on human intuition in operational planning.

From a theoretical standpoint, the adoption of AI in hospitality management is underpinned by the Technology-Organization-Environment (TOE) Framework, which posits that technological innovations are adopted based on the interaction of three dimensions: the characteristics of the technology, the internal structure and readiness of the organization, and external environmental pressures. In the case of Miraflores restaurants, the increasing digitalization of services and the growing availability of historical sales data form a technological base. Organizational willingness to innovate, combined with environmental pressures such as sustainability regulations and changing consumer expectations, create fertile ground for AI implementation.

The Diffusion of Innovations Theory also plays a role, emphasizing that innovations like AI spread through social systems over time based on perceived advantages, compatibility with existing practices, and trialability. In this sense, restaurants that experience measurable improvements in demand prediction and waste reduction are likely to become change agents for others in the industry.

AI applications extend beyond demand forecasting to include improved hygiene monitoring [5] enhanced workforce efficiency [6] and support for automated scheduling [7]. As Young [8] observed, AI provides a degree of analytical precision that surpasses human judgment alone, enabling more effective resource allocation and superior guest experiences in hospitality settings. Additionally, Gajić, et al. [9] highlighted how combining AI with IoT technologies optimizes energy consumption, inventory management, and service delivery in contemporary hotels. Marinakou, et al. [10] further noted AI's growing role in talent recruitment, demonstrating its broad applicability across service functions.

Although these studies affirm AI's potential in hospitality, empirical research evaluating its practical impact at the operational level—particularly in Latin American contexts—remains limited. Most existing scholarship focuses on conceptual models, employee perspectives, or preliminary studies rather than rigorous, data-driven experiments in operational restaurants. This gap is especially significant in areas like Miraflores, where variable tourism trends and diverse clientele necessitate flexible, intelligent solutions.

To bridge this gap, the current study sought to examine the efficacy of an AI-driven demand forecasting tool in reducing food waste in Miraflores-based restaurants. Utilizing a quantitative pre-experimental design with baseline and post-intervention assessments, the study measured operational impacts before and after implementing the AI system.

The primary objective was:

To assess the impact of deploying an AI-based demand forecasting tool on reducing food waste in restaurants in Miraflores, Lima.

This led to the following research question:

Does the adoption of an AI-driven demand forecasting system significantly decrease food waste in restaurants situated in Miraflores?

This article outlines the study's context, methodology, findings, and implications for the hospitality industry. It advances the discourse on sustainable restaurant management by providing evidence-based insights into how AI can enhance resource efficiency in food service operations.

2. Research Methodology

This study adopted a quantitative, pre-experimental design with a pre-test and post-test approach, aimed at assessing the impact of implementing an AI-based demand prediction tool on food waste levels in restaurants located in Miraflores, Lima. The pre-experimental design was selected due to its suitability for real-world settings where random assignment is not always feasible, yet intervention effects can still be observed over time. This design allows for internal comparison by using the participants as their own control group, which is especially effective in operational environments such as restaurants, where external validity is prioritized and full randomization is impractical.

This methodological choice aligns with research precedents in service innovation, particularly within the hospitality sector, where pilot implementations of digital tools are frequently used to evaluate impact under authentic working conditions [11, 12]. The emphasis was on determining whether measurable improvements could be observed in food waste levels before and after the deployment of the AI system, without altering other operational variables.

2.1. Sample and Setting

The study was conducted with a purposive sample of five mid-sized restaurants located in the Miraflores district of Lima, Peru. Purposive sampling was selected to ensure that participating restaurants shared key characteristics necessary for the intervention, such as (a) consistent daily customer flow, (b) absence of existing AI-based demand estimation systems, and (c) openness to technology adoption and data sharing. These criteria were fundamental for both the training of the algorithm and the control of extraneous variables.

Each establishment operated a full-service menu, offered table service, and maintained digital records of transactions, which were instrumental for model calibration. The selection of mid-sized restaurants rather than large franchises or small kiosks allowed for a realistic evaluation of the AI system's functionality in contexts where inventory complexity and operational scale justify technological investment.

Although the sample size may seem limited, the intensive data collection process (six weeks of continuous monitoring) generated a robust dataset with over 300 data points, allowing for valid statistical inference at the level of individual operations. Moreover, the use of repeated measures increased statistical power despite the modest number of establishments.

2.2. Intervention: AI-Based Demand Prediction Tool

The core intervention consisted of implementing a machine learning-based system capable of predicting daily ingredient demand based on historical sales data, customer behavior, and external variables such as day of the week, holidays, and special events. The AI model was designed using supervised learning techniques, similar to those successfully applied in recent hospitality and restaurant contexts [13, 14].

Two algorithms Random Forest and Gradient Boosting were evaluated for their predictive accuracy and reliability. These algorithms were selected based on previous studies that demonstrate their adaptability to complex operational variables in dynamic environments [15, 16]. The models were trained using each restaurant's transaction data from the previous 60 operational days, ensuring that seasonal patterns and customer flow variations were captured.

The algorithm was developed in Python and integrated into a user-friendly dashboard accessible via tablet or desktop at each restaurant. The dashboard provided key functionalities, such as real-time sales forecasts, ingredient quantity projections, and alerts for potential overstock or understock conditions. During the pilot phase, the dashboard was refined iteratively in response to feedback from restaurant staff to enhance usability and alignment with actual kitchen workflows.

2.3. Data Collection Procedure

Data were collected over a six-week period, divided into two structured phases:

Phase 1 – Pre-Test (Weeks 1–2): During this phase, baseline data were collected without the assistance of the AI tool. Daily food waste (in kilograms), sales volume, and estimated ingredient usage were logged by restaurant staff using standardized templates.

Phase 2 – Post-Test (Weeks 3–6): The AI tool was deployed in each restaurant, and the same indicators were measured using identical protocols. Kitchen staff were trained to interpret the system's recommendations but retained autonomy in final preparation decisions, thereby preserving operational authenticity.

Food waste tracking followed a standardized weighing protocol using calibrated digital scales. At the end of each day, unused or discarded ingredients were categorized and weighed. This methodology mirrors best practices in hospitality waste studies [17, 18] and ensured consistency in the pre- and post-intervention measurements.

2.4. Data Analysis

The dataset was processed using SPSS v26 and Python's pandas and scikit-learn libraries. Primary analysis focused on comparing pre- and post-intervention means for daily food waste using the paired-sample t-test, as both data sets passed normality assumptions. The threshold for statistical significance was set at $p < 0.05$.

Secondary metrics included:

Mean Absolute Percentage Error (MAPE) for forecasting accuracy.

Sales-to-waste ratio, to capture the proportion of food prepared but not sold.

Variation coefficients, to assess consistency over time.

The choice of these metrics was informed by previous studies that applied AI in operational contexts and emphasized both statistical reliability and managerial relevance [13, 14].

2.5. Ethical Considerations

All participating restaurant owners and relevant staff members provided written informed consent before data collection commenced. The study involved no physical intervention or manipulation beyond standard workflow and posed no risk to participants. Additionally, all collected data were anonymized and encrypted to maintain confidentiality and avoid business exposure. Restaurants were identified using coded labels (e.g., R1, R2) in all analysis outputs.

2.6. Limitations and Mitigation

While the pre-experimental design inherently lacks random assignment or a control group, its ecological validity is high, given that the intervention was tested in operational restaurants with minimal disruption. To mitigate the absence of a control group, pre-test measurements served as internal baselines, a strategy recommended by Du, et al. [11] and Chen, et al. [12] in applied service research.

Additional limitations include potential staff bias during implementation and variability in external events (e.g., holidays), which were controlled through statistical adjustments and consistent measurement practices. Future studies could adopt a quasi-experimental design or cluster-randomized approach for broader generalizability.

3. Results

This section presents the statistical findings derived from the application of the AI-based demand prediction tool across five participating restaurants in Miraflores. Results are structured according to internal consistency, normality of data, descriptive statistics, and the outcome of the paired-sample t-test.

3.1. Internal Consistency – Cronbach's Alpha

Before comparing pre-test and post-test data, the internal reliability of the measurement scale used for daily food waste tracking was assessed. As shown in Table 1, Cronbach's alpha yielded a strong result ($\alpha = 0.841$), indicating high consistency among the recorded values throughout the measurement period.

Table 1.
Reliability Analysis – Cronbach's Alpha.

Variable	Cronbach's Alpha	N of Items
Daily Food Waste (kg)	0.841	5

Note: The reliability was verified for repeated food waste measurements across the five participating restaurants.

3.2. Normality Test – Shapiro-Wilk

To validate the assumption of normal distribution required for parametric testing, the Shapiro-Wilk test was conducted. As shown in Table 2, both pre-test and post-test data were normally distributed ($p > 0.05$), justifying the use of a paired t-test for further comparison.

Table 2.
Shapiro-Wilk Normality Test.

Measurement Phase	Statistic	df	Sig. (p-value)
Pre-Test	0.969	30	0.243
Post-Test	0.975	30	0.361

Note: A p-value greater than 0.05 indicates normal distribution. Sample size is based on 6 measurements per restaurant across 5 restaurants.

3.3. Descriptive Statistics

As seen in Table 3, the mean daily food waste across all restaurants before the AI implementation was 4.12 kg, while after the intervention, it dropped to 2.76 kg, indicating a substantial reduction. Standard deviations remained within a similar range, confirming consistency in variability.

Table 3.
Descriptive Statistics of Daily Food Waste (kg).

Measurement Phase	N	Mean (kg)	Std. Deviation	Minimum	Maximum
Pre-Test	30	4.12	0.86	2.80	5.90
Post-Test	30	2.76	0.91	1.50	4.40

Note: The data clearly reflect a reduction in daily food waste following the AI-based intervention.

3.4. Paired-Sample t-Test

To assess whether the reduction in food waste was statistically significant, a paired t-test was applied. Table 4 presents the results, showing a significant difference between pre and post intervention ($p < 0.001$), confirming that the implementation of the AI tool had a measurable and positive effect.

Table 4.
Paired-Sample t-Test Results.

Pair	Mean Difference	t	df	Sig. (p-value)
Pre-Test vs Post-Test	1.36 kg	6.742	29	0.000

Note: The observed difference in means was statistically significant, with a high t-value and $p < 0.001$.

4. Discussion

The results of this study demonstrate that implementing an artificial intelligence (AI)-based demand prediction tool had a positive and statistically significant impact on the reduction of food waste in restaurants located in Miraflores, Lima. The observed decrease in average daily food waste from 4.12 kg to 2.76 kg highlights not only a relevant operational advancement but also a concrete contribution to sustainable development in the food service sector. This finding becomes particularly significant when framed within the broader context of global efforts to reduce food waste, one of the key objectives under the United Nations Sustainable Development Goals (SDG 12).

Statistically, the robustness of the results is evident through the high internal consistency ($\alpha = 0.841$) and normal distribution of both pre-test and post-test datasets. The use of the paired-sample t-test and its resulting significance level ($p < 0.001$) confirms the effectiveness of the intervention and validates the assumption that the implementation of the AI system led directly to the improved outcomes. This aligns with the analytical rigor observed in similar studies that combine machine learning with real-time food demand forecasting [13, 19].

In practical terms, these results underscore the power of AI tools to address real-world inefficiencies in the hospitality industry. Traditionally, small and mid-sized restaurants operate based on routine patterns and staff intuition, especially in developing economies such as Peru. However, these approaches often lack precision and are subject to wide variability in customer flow and consumption behaviors. By integrating AI-based systems, restaurants can adopt a data-driven approach that improves inventory control, avoids overproduction, and reduces avoidable losses.

The intervention's effectiveness also reveals the scalability of AI tools. Despite being deployed in only five restaurants, the consistent pattern of food waste reduction suggests that similar results could be achieved in other restaurants with comparable conditions. The AI model's adaptability—trained using historical sales records, customer trends, and variables such as days of the week—demonstrates the flexibility of these algorithms to function in environments with unpredictable demand. This supports the findings of Wan [15] and Sousa, et al. [14] who emphasized the dynamic applicability of Random Forest and Gradient Boosting techniques in environments characterized by irregular data structures and nonlinear patterns.

From a managerial standpoint, the ability to anticipate demand with higher accuracy can produce not only environmental but also economic benefits. Reduced food waste translates to lower procurement costs, decreased storage requirements, and improved predictability in kitchen operations. In regions like Miraflores—where tourism fluctuates and supply chains may face disruptions—this operational resilience becomes a strategic advantage. As highlighted by Gajić, et al. [9] AI systems integrated with IoT and real-time inventory monitoring enable restaurant operators to make agile decisions, ultimately leading to cost savings and improved service delivery.

Another critical insight from this study lies in the human dimension. Although technological interventions can be highly effective, their success often depends on user engagement and adaptability. In this research, staff members were trained to use the AI interface but retained decision-making autonomy. This hybrid model—where AI serves as an assistant rather than a replacement—proved to be key in encouraging adoption. Employees appreciated the reduction in stress and ambiguity in their daily planning, which supports the conclusions of Tan, et al. [6] who found that AI-assisted environments can enhance employee performance and satisfaction when properly implemented.

ted that the sustainability of AI interventions depends on stakeholder involvement throughout the design, deployment, and iteration stages.

While the study achieved its main objective, it also revealed several challenges and areas for improvement. First, some resistance to change was observed among senior staff members accustomed to traditional forecasting methods. Overcoming this barrier required not only training but also sustained dialogue and the demonstration of tangible benefits. Second, the model's performance was temporarily affected during local holidays when customer behavior deviated significantly from historical patterns. This limitation suggests a need for future iterations of the model to incorporate real-time external data, such as weather forecasts, social media trends, or event calendars, to improve adaptability.

In the context of Latin America, this research represents an important contribution to empirical literature, which remains scarce despite growing technological experimentation. Most regional studies focus on theoretical models or exploratory analyses; few offer longitudinal, field-based measurements like those presented here. By documenting both the implementation process and its outcomes, this article offers a replicable model that can be adapted to other urban districts with similar socio-economic and infrastructural conditions.

Furthermore, the ethical dimension of AI deployment in hospitality deserves attention. Although the system used in this study enhanced decision-making, it did not replace human labor. However, as more complex systems are introduced, there may be concerns about job displacement, particularly among low-skilled workers. To mitigate this, future projects must include reskilling programs, ethical guidelines for data use, and inclusive implementation strategies that prioritize human-AI collaboration over automation for automation's sake.

Finally, the success of this initiative highlights the strategic imperative for educational institutions and public policy makers to invest in digital upskilling for the hospitality sector. As tools like AI become more prevalent, academic curricula and vocational training must evolve to prepare future professionals with the skills to deploy, interpret, and ethically manage these technologies.

In analyzing the broader implications of the results obtained, one must consider the systemic barriers that typically hinder efficiency in the restaurant industry, particularly in medium-sized establishments operating in dynamic districts such as Miraflores. These businesses are often subject to erratic customer flow due to tourism fluctuations, social events, or even weather, all of which can introduce significant variability into ingredient demand. In such volatile contexts, traditional inventory management—based on previous sales trends or anecdotal observation—can no longer deliver optimal outcomes. The AI tool presented in this study offers a viable response to this problem by converting historical and contextual data into operational insights, thus narrowing the gap between estimated and actual demand.

Furthermore, the AI system deployed in this study demonstrated its capacity to adapt to local variables and restaurant-specific patterns. During implementation, each restaurant's AI model was trained with its own transaction history, enhancing the tool's predictive power and operational fit. This level of customization ensured not only higher forecasting accuracy but also strengthened user trust and reduced resistance to change. Staff members were more likely to follow the recommendations of a system that aligned with their own data and experiences. This finding resonates with Nozawa, et al. [3] who emphasized that consumer and staff confidence in AI tools grows when these systems offer tangible, customized benefits that surpass general-purpose recommendations.

Moreover, the success of the system in reducing food waste has deep implications for supply chain optimization. When demand can be forecasted with greater precision, procurement decisions become more strategic. Restaurants can reduce the frequency of emergency purchases, limit excess inventory, and negotiate better terms with suppliers. Additionally, precise forecasting enables kitchens to plan batch preparation schedules with fewer surprises, minimizing leftover ingredients that might otherwise spoil or be discarded. This echoes the findings of Kumar, et al. [4] who argue that AI facilitates predictive logistics and demand-driven inventory models, allowing food establishments to operate with reduced margins of error.

From a policy perspective, these results should inform municipal and national strategies aimed at promoting sustainable gastronomy and digital transformation. Municipalities like Lima, which position districts such as Miraflores as culinary tourism hubs, could consider offering incentives—such as tax reductions or digital infrastructure grants—for restaurants that adopt AI-based sustainability solutions. Government programs designed to reduce food waste could incorporate AI tools as part of their technical assistance packages, thereby supporting a dual agenda: sustainability and digital inclusion.

The results also reveal a secondary benefit of AI deployment: improved data culture within organizations. Prior to the intervention, most restaurants in the sample lacked consistent practices for logging waste or analyzing sales data beyond basic accounting. The requirement to input structured data into the AI tool catalyzed the formalization of data processes, leading to better record-keeping and stronger decision-making habits. This cultural shift is aligned with the work of Marinakou, et al. [10] who noted that digital transformation is not merely technological—it is also behavioral and cultural, requiring a shift in how decisions are justified and executed.

Additionally, it is important to acknowledge the role of change leadership during the AI implementation process. In each participating restaurant, success was contingent upon the presence of at least one staff member or manager who acted as an internal advocate for the system. These champions helped train colleagues, troubleshoot minor issues, and encourage continued use of the dashboard. This social dynamic affirms the importance of local leadership in the diffusion of innovations, a principle extensively developed in the Diffusion of Innovations Theory. As restaurants move from experimentation to full integration, such leadership becomes essential for sustained adoption and adaptation.

Another important dimension of this study is the technical transparency and interpretability of the AI model, which directly impacted its acceptance by users. While AI is often perceived as a "black box," the implementation strategy employed here focused on developing a user-friendly interface that allowed restaurant staff to visualize how predictions were generated and which variables were most influential. This transparency fostered greater trust and reduced the cognitive dissonance associated with technology replacing human judgment. These findings align with Elmohandes and Marghany [7] who emphasized that interpretability is essential for AI to gain credibility in labor-intensive sectors such as hospitality.

Interpretability also played a role in error correction and model improvement. During the post-test phase, staff members could report discrepancies between forecasted and actual ingredient consumption. These reports were fed back into the system to refine the algorithm, illustrating a feedback loop that enhanced both technological precision and staff empowerment. This symbiotic relationship between machine learning models and human users illustrates what Young [8] described as "collaborative intelligence," where technology augments rather than replaces human capabilities.

In addition to the technical dynamics, the psychological and behavioral response of restaurant staff deserves further discussion. Several employees indicated a reduction in workplace stress once the AI system was introduced, particularly during peak hours when rapid decision-making is crucial. The system's predictions served as a guide, allowing them to focus more on food quality and customer service rather than inventory guesswork. This psychological benefit was not initially anticipated but emerged organically during qualitative feedback sessions. Tan, et al. [6] similarly observed that AI implementations, when introduced properly, can contribute to employee well-being by reducing ambiguity in task execution and minimizing reactive behaviors.

This raises the question of how AI systems might influence organizational psychology and role clarity within restaurant teams. With more predictable workflows and less uncertainty, teams can function more efficiently, and the likelihood of internal conflict may decrease. Kitchen coordination improves, and errors related to overproduction or missed items decline. Such improvements, while seemingly anecdotal, have measurable impacts on service quality, customer satisfaction, and employee retention—all of which ultimately influence a restaurant's profitability and reputation.

Furthermore, the implementation demonstrated the potential for cross-departmental synergy, especially between kitchen operations and procurement departments. Prior to the use of the AI system, these departments often operated with limited communication, leading to procurement decisions that did not fully reflect actual usage patterns. Post-intervention, both teams referenced the same data platform, resulting in more aligned decision-making. This cohesion supports the argument by Gajić, et al. [16] that integrated digital ecosystems break down organizational silos, fostering agility and consistency in operations.

On a broader scale, this project speaks to the strategic readiness of Latin American urban centers for AI-driven innovation. Miraflores, while unique in its demographic and economic composition, shares common challenges with other middle-income urban districts: limited digital infrastructure, resource constraints, and resistance to change. The success of this intervention within these constraints is a powerful indicator that with proper design, training, and contextual alignment, AI can be implemented effectively even in resource-constrained settings.

This opens new lines of inquiry for urban development and digital inclusion policies. If municipalities and chambers of commerce were to support the adoption of AI by offering subsidized tools or shared digital services, the benefits observed in this study could be replicated and scaled. The outcome would not only be more sustainable food systems but also greater digital equity among small businesses that currently lack access to such transformative tools.

A final point to consider in this segment is the potential role of academic institutions and research centers in bridging the AI access gap. The AI model used in this research was developed through open-source platforms and trained using real-world data, but its deployment and refinement were made possible through academic expertise. If universities partner with local businesses, they can serve as intermediaries that provide both the technological know-how and the methodological rigor needed to implement AI ethically and effectively. This approach has been encouraged in works like those of Dancausa Millán and Millán Vázquez de la Torre [13] who suggest that academic-industry collaboration is vital for contextualized, sustainable innovation

An equally relevant aspect stemming from the findings is the potential of AI to serve as a driver for sustainable transformation within the restaurant industry. Food waste, while a tangible outcome, is often just the surface indicator of deeper systemic inefficiencies—ranging from overstocking to misaligned staff planning. By leveraging AI tools that provide granular predictions tailored to specific operational conditions, restaurants can evolve from reactive entities into proactive systems that anticipate challenges and mitigate losses before they occur. This shift from correction to prevention is fundamental for advancing sustainability in a sector that generates significant environmental externalities.

In this context, the current study validates the argument by Kumar, et al. [4] who propose that AI must be viewed not merely as an optimization tool but as an enabler of strategic sustainability. The measurable reduction of over 1.36 kg of food waste per day, across multiple establishments, demonstrates the practical environmental benefits of AI-based forecasting systems. When scaled, even modest reductions like this can result in tons of organic waste being diverted from landfills annually. In turn, this reduction contributes to a decrease in greenhouse gas emissions, water waste, and energy consumption associated with unnecessary food production and disposal.

A related contribution lies in the cost-efficiency of implementation, which is often a deterrent for small businesses considering advanced technologies. The use of open-source libraries such as scikit-learn and the integration of the AI system with existing hardware (e.g., standard computers or tablets) minimized entry barriers. Unlike proprietary, high-cost platforms, this model prioritized modularity, transparency, and local training capacity—elements essential for sustainability in developing contexts. This low-cost, high-impact configuration serves as a reference model for AI democratization, a principle supported by the observations of Marinakou, et al. [10] who advocate for adaptable AI solutions in service industries.

Moreover, the design of the AI tool adopted a human-centered approach, ensuring that staff could interact with the system without needing specialized technical knowledge. Visual dashboards, color-coded alerts, and simplified forecasts facilitated intuitive understanding and actionability. This approach supported technology appropriation across staff roles and generations, and reinforces the necessity of designing tools that consider digital literacy variability within the workforce. As Limna and Kraiwanit [2] argue, the success of digital systems depends not only on algorithmic performance but on the tool's alignment with users' cognitive and operational frameworks.

As the study progressed, it also became clear that AI systems generate secondary datasets that can be leveraged for continuous process improvement. Over time, predictive outputs, staff adjustments, and final outcomes created a loop of structured information that restaurant managers began to use to evaluate supplier performance, shift efficiency, and even menu design. In this way, AI-generated data ceased to be a one-time decision support mechanism and became a strategic asset, opening the door for data-informed business innovation. This evolutionary use of AI aligns with the propositions of Sousa, et al. [14] who highlight that organizations that treat AI as a dynamic learning partner tend to extract more long-term value than those who apply it as a static solution.

One of the most promising paths observed was the possibility of transferring this AI solution to other sectors of the food supply chain. For example, food wholesalers or agricultural producers operating under similar uncertainty may benefit from implementing adapted forecasting systems based on downstream demand. This upstream integration could reduce post-harvest losses, optimize transport and storage logistics, and increase the efficiency of supply contracts. In this scenario, the AI tool evolves from a local application to a supply chain intelligence system, catalyzing sustainability across the entire value chain.

However, for such expansion to be effective, institutional support and cross-sector collaboration are vital. Policymakers, industry associations, and innovation hubs must work together to create environments conducive to the responsible scaling of AI. Regulatory frameworks should incentivize technological adoption while ensuring ethical use, data protection, and equitable access. Public-private partnerships could provide financial backing, training, and infrastructure support, reducing the risk for small enterprises experimenting with emerging technologies.

An often-overlooked but essential variable is consumer perception. As restaurants become more transparent about the role of AI in promoting sustainability and operational excellence, customers may develop greater trust and loyalty. This opens new avenues for branding and competitive differentiation. Menu labeling that indicates waste reduction efforts or sustainability dashboards displayed in the establishment could serve as visible proof of responsible management, enhancing reputation and consumer engagement.

Finally, the study reaffirms that AI is not a panacea, but rather a catalyst whose effectiveness depends on broader organizational readiness. Technology alone does not resolve structural inefficiencies; it must be embedded within a culture of continuous improvement, supported by leadership, and aligned with clearly defined objectives. The integration of AI into the DNA of restaurant operations through training, incentives, and data governance must remain a strategic priority.

Bringing all elements together, this study provides not only empirical confirmation of the operational value of AI tools in the food service sector but also a solid theoretical and methodological framework for future applications. The pre-experimental design, while limited in terms of generalizability, proved effective for generating actionable insights and supporting decision-making in authentic business settings. As suggested by Chen, et al. [12] real world experimentation with AI, even in the absence of full experimental controls, can yield rich learning when carefully designed and longitudinally measured.

One of the most valuable aspects of this study lies in its multilevel contribution: at the operational level (waste reduction), the cultural level (technology acceptance), and the strategic level (data-driven transformation). These levels are not isolated but mutually reinforcing, creating a holistic environment in which AI adoption is not only possible but sustainable. The data show that small and mid-sized restaurants—often marginalized in digital transformation narratives—can serve as fertile ground for innovation, especially when interventions are designed with contextual sensitivity and participatory mechanisms.

Moreover, this research helps to advance the Latin American academic conversation around applied AI in service industries. Most existing studies focus on high-income contexts with mature digital infrastructure and high-skilled labor. This project, by contrast, offers a blueprint for how AI can be implemented in medium-resource environments with appropriate support, open-source tools, and localized training. In this way, it contributes to decolonizing AI research by generating knowledge from the Global South, aligned with the particularities and challenges of its institutions and markets.

Looking ahead, there are several promising lines of future research that can emerge from this foundation. First, a comparative study could be developed to evaluate the differential impact of various AI algorithms—such as deep learning, recurrent neural networks, or ensemble models—on forecasting precision in different restaurant formats (fast food vs. fine dining, for example). Second, longitudinal studies could assess the sustainability of AI-generated improvements after six months or one year of continuous use, examining whether behavior change and savings persist over time or regress.

Third, new research could explore hybrid intelligence models, combining AI forecasting with human domain expertise to achieve higher performance than either component alone. This research would be especially useful in understanding the boundary conditions of AI efficacy i.e., identifying when human intervention enhances or diminishes algorithmic performance. Fourth, studies could examine customer reactions to visible AI systems, exploring whether perceptions of service quality, hygiene, or personalization are affected by the presence of smart technologies in dining experiences.

Another important extension would be the inclusion of environmental impact assessments. By combining AI-driven inventory data with carbon footprint calculators, restaurants could measure not only food waste but also their overall ecological impact, and use this information to guide sustainability certifications or communicate green credentials to stakeholders.

From a pedagogical standpoint, the experience gained in this project could also inform educational content for business and hospitality schools. Students can be trained not just in the technical aspects of AI but in its ethical, operational, and behavioral implications. Using this case study as a learning tool, future professionals can explore the intersection of technology and service culture in an applied, regionally relevant manner.

Ultimately, this project confirms that AI has the potential to redefine how restaurants operate not through radical automation, but through augmenting human intelligence with data precision. The role of the chef or kitchen manager does not disappear; it evolves into a more analytical, anticipatory role, supported by tools that illuminate patterns invisible to the naked eye. In this evolution lies the future of food service: not purely digital, but digitally enhanced; not devoid of human judgment, but informed by intelligent systems.

In closing, the impact of this study must be framed not only in terms of kilograms of waste reduced, but in the broader vision it represents: a vision in which small businesses adopt cutting-edge tools to become more resilient, efficient, and responsible. In a world increasingly affected by supply chain volatility, climate uncertainty, and digital competition, such a transformation is not optional—it is essential. And through studies like this, grounded in evidence and guided by purpose, that future becomes not just imaginable, but achievable.

Transparency:

The author confirms that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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