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Food Waste Reduction AI Technologies in Restaurant Management: An MS-TORO Approach

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Abstract

This study analyzes artificial intelligence (AI)-based technologies for food waste reduction in restaurant management, particularly in the case of the Philippines. Using the multiple-stakeholder target-oriented robust-optimization (MS-TORO) approach, AI solutions are ranked based on cost, feasibility, infrastructure requirements, and effectiveness. The key findings highlight that Too Good To Go is the most practical AI solution due to its affordability and focus on surplus food redistribution, making it ideal for resource-limited settings. The study emphasizes the need for government support, financial incentives, and public–private partnerships to facilitate AI adoption. Additionally, integrating AI-driven waste reduction with food security initiatives and sustainability projects can enhance their impact. Addressing economic and infrastructural challenges is crucial for maximizing AI's potential in food waste management in developing economies.

Keywords: food waste; restaurant management; MS-TORO approach; developing country

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Academic Editors: José Agustín Tapia Hernández, Francisco Rodríguez-Félix and Xiong Luo

Received: 15 April 2025
Revised: 9 May 2025
Accepted: 26 May 2025
Published: 30 July 2025

Citation: Cejas, R. Food Waste Reduction AI Technologies in Restaurant Management: An MS-TORO Approach. *Processes* **2025**, *13*, 2419. https://doi.org/10.3390/pr13082419

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1. Introduction

Food waste reduction efforts in restaurants remain a major concern for managers, given the extensive resources required to carry out such goals while ensuring operational efficiency is achieved [1]. While there is already a growing number of technologies that aid in food waste reduction, there remains a lack of studies in the literature that evaluate the effectiveness of such food waste prevention solutions. Much more so, the viability of these technologies has not yet been explored as of date. It is a known strategy in the literature that the analysis of technology management is modeled after Multiple Criteria Decision Making (MCDM) techniques. MCDM tools have been widely applied in restaurant management and the broader hospitality industry, including the following: restaurant review analysis using game theory and sentiment analysis [2], location analysis using analytical hierarchy process (AHP) [3], business model analysis using decision making trial and evaluation laboratory and analytic network process (DEMATEL-ANP) [4], restaurant location prioritization via hexagonal fuzzy AHP [5], and sustainable hyper-local restaurants under best–worst method (BWM) and hesitant fuzzy shapely order weights average (HSFOWA) approach [6], among others. However, none of these works in the literature has specifically analyzed food waste reduction technologies. Assessing the most effective technologies for reducing food waste is vital for achieving environmental sustainability, economic efficiency, and food security [7,8]. Food waste generates greenhouse gas emissions, especially methane from landfills, which makes the implementation of effective reduction technologies essential for decreasing the carbon footprint. Furthermore, food production demands considerable resources such as land, water, and energy, so decreasing

waste is important for conserving these crucial inputs [9,10]. From an economic standpoint, minimizing food waste offers advantages to businesses, consumers, and governments by lowering costs linked to food production, storage, and disposal. It is also instrumental in tackling global hunger, as reducing food waste increases the availability of food for those in need. Analyzing the effectiveness of various technologies facilitates improved scalability and efficiency, allowing solutions to be customized for specific environments such as homes, restaurants, or supermarkets. Additionally, governments can leverage this analysis to back policies that encourage the adoption of the most effective practices. Ultimately, comprehending which technologies are most effective aids in creating systems that resonate with consumer habits and cultural norms, fostering wider acceptance and sustained success in food waste reduction. Fortunately, a recently developed MCDM tool can satisfactorily be designed to address complex decision-making scenarios involving diverse stakeholder interests and inherent uncertainties. This methodology integrates the objectives of various stakeholders into a unified optimization framework, ensuring that solutions are both robust against uncertainties and aligned with stakeholder goals [11].

Due to these major research gaps in the literature, this paper aims to implement the MS-TORO framework in the selection of alternative technology for food waste reduction in restaurants. In order to demonstrate the applicability of the model, a case study in the Philippines is performed. The following research questions are intended to be addressed:

Research question 1: Which of the alternative AI technologies for food waste reduction in restaurants must be selected considering the diverse interests of stakeholders as well as the system constraints?

Research question 2: What is the ranking of preference for AI technologies according to the interests of stakeholders as well as the system constraints?

Research question 3: How does the preference for AI technology shift with respect to changing uncertainty levels?

In summary, this paper provides a novel addition to the existing literature by being the first to implement the MS-TORO framework in assessing AI technologies aimed at reducing food waste in restaurant settings. Although various MCDM methods have been used in this sector, none have specifically focused on the selection of technologies for preventing food waste, particularly in restaurants. This study distinctively combines the varied interests of stakeholders with system limitations in the decision-making framework, tackling the complexity of practical application that is often neglected. Additionally, it builds upon previous research by including uncertainty modeling to evaluate how preferences for AI technologies change under varying conditions. Through a case study carried out in the Philippines, this paper also addresses a geographical and contextual gap by offering insights from the perspective of a developing nation. Collectively, these contributions present a thorough and innovative methodology for selecting technologies that promote sustainable operations in restaurants.

2. Background of Analysis

In the overall function of restaurant management, from planning, organizing, motivating, and controlling to achieve business goals and improve efficiency, a sound and comprehensive decision-making process and control must be established to ensure technical progress, innovation, and adherence to principles and standards [12,13]. With the ever-growing concern about restaurant stakeholders' adherence to sustainable management practices, several strategies are being put forward to address significant environmental and economic issues in restaurant management, particularly in food waste reduction. Menu planning, sourcing, preparation, and customer service are key areas for implementing waste reduction strategies in restaurants [14]. To ensure success in food waste reduction,

stakeholders are moved to develop more systematic management, improved skills, and integration of circular economy principles. While progress has been made, further research is needed to develop context-specific solutions and overcome barriers to implementation, particularly in different geographical settings [14,15]. On the other hand, considering that food waste management is a rather broad spectrum consisting of several functions and operations, technologies such as machine learning and artificial intelligence (AI) can be used to enhance competitiveness and adapt to changing market conditions. Furthermore, machine learning is found to be useful in predicting waste, managing inventory, and suggesting new recipes using near-expiry ingredients [16]. Specifically, for AI-based technologies, such tools have proven to provide a new perspective in revolutionizing restaurant management by enhancing efficiency, reducing costs, and improving customer satisfaction. AI-powered solutions can optimize inventory management while predicting demand and minimizing food waste by analyzing expiration dates and recommending new recipes [16,17]. Aside from that, machine learning and data mining techniques enable restaurants to analyze consumer behavior, personalized menus, and tailor marketing campaigns [18,19]. AI-driven chatbots and virtual assistants streamline order-taking and customer inquiries, while humanoid robots are being explored to further enhance the dining experience [19]. These technologies help restaurants address challenges such as labor shortages and changing consumer preferences, particularly among Generation Z [18]. However, the integration of AI in restaurant management also presents potential ethical considerations and implementation challenges that need to be addressed [17].

Some of the technology-based solutions developed to aid in food waste reduction have gained popularity in the literature, according to a comprehensive scan of Scopus articles in the past five years. For one, Winnow Vision, developed by Winnow Solutions, focused on assisting businesses in reducing food waste and improving efficiency [20]. This tool aims to save costs and support environmental sustainability through its AI-driven solutions to tackle food waste in commercial kitchens. By providing real-time data and insights, it enables kitchens to identify waste sources, modify portion sizes, and implement waste reduction techniques. Empirically, it was found that a restaurant that adopted Winnow Solutions experienced a 30% decrease in food waste within just a few months. For another, Leanpath and Kitro have also provided technologies powered by AI to be incorporated into current kitchen processes to observe and assess food consumption in real time. By monitoring the amount and variety of food waste, AI systems offer valuable information that assists kitchen personnel in modifying portion sizes, enhancing inventory control, and minimizing excessive preparation [21,22]. A summary table of these AI technologies can be found in Table 1.

In terms of SMEs, sustainability needs, government support, and public–private partnerships, AI technologies in AI restaurant management also prove essential. For example, the adoption of AI technologies in SMEs faces significant barriers, including limited financial resources, lack of technical expertise, and resistance to change [23]. Additional challenges include fear of losing control over critical business processes and a perceived lack of IT maturity [24]. Despite these obstacles, AI can enhance operational efficiency, product development, and competitive advantage for SMEs [23]. To overcome adoption barriers, researchers propose various strategies such as government incentives, public–private partnerships, and targeted training programs. In fact, Ref. [25] suggest a phased framework for AI adoption, starting with low-cost, general-purpose tools and progressing to more advanced applications. On the other hand, Ref. [26] emphasize the need for a pragmatic framework addressing cost constraints and skill deficiencies. Successfully implementing AI in SMEs can lead to significant benefits and positive socioeconomic impacts, highlighting its transformative potential in this sector.

Table 1. AI technologies for food waste reduction.

Feature	Winnow Vision	Leanpath	Too Good To Go	Kitro
Primary focus	Food waste tracking in commercial kitchens	Food waste tracking and prevention in food service	Reducing food waste at the consumer/retail level	Food waste measurement and analytics
Technology	AI Computer vision	Smart scales with visual tracking	Mobile app for surplus food	Smart bin with AI image recognition
Target market	Hotels, restaurants, large kitchens	Foodservice, corporate cafeterias	Consumers, restaurants, supermarkets	Commercial kitchens
Function	Camera and scale logs waste and software analyzes the data	Staff input data and software provide insight	Businesses sell surplus food via the app	Smart bin captures data on waste and analyzes them
Data and reporting	Dashboard Analytics	Real-time dashboards and reports	Consumer-facing app statistics	Custom waste reports and key performance indicators

To model food waste management as an MCDM tool, the fuzzy set theory can be further integrated to maximize the benefits of the decision-making process. Specifically, fuzzy MCDM approaches have been used to develop decision-support models for restaurant menu management, addressing challenges in menu analysis and engineering [27]. Stochastic MCDM methods have been employed to evaluate restaurant service quality, helping businesses understand their competitive position based on consumer opinions [28]. A systematic review of MCDM techniques in the tourism and hospitality industry revealed that integrated techniques, AHP, and fuzzy AHP were among the most commonly used methods, with the airline industry being a prominent application area for service quality evaluation [29]. In restaurant management, MCDM has been used for menu analysis and engineering, with fuzzy MCDM addressing imprecision in input parameters [27]. The integration of sentiment analysis with MCDM allows for the incorporation of natural language reviews in decision-making processes, as demonstrated in a study using TripAdvisor reviews for restaurant choice [30]. MCDM methods have wide applications in marketing and business management, including product positioning, market segmentation, and strategic planning [31]. The use of MCDM in these fields provides a transparent and objective approach to decision-making, with ongoing refinement and integration of new technologies promising to enhance its effectiveness in the dynamic business landscape. Among these MCDM tools, a recently developed technique allows for the integration of multiple stakeholders' interests in decision-making—that is, the Multiple Stakeholder-based Target-Oriented Robust Optimization (MS-TORO) framework [32]. MS-TORO approach is a decision-making model aimed at solving intricate issues that involve various stakeholders with differing goals and uncertainties [33–35]. By merging robust optimization methods with target-focused modeling, MS-TORO guarantees that the solutions are congruent with the varied objectives of stakeholders while ensuring resilience under uncertain conditions. In contrast to conventional optimization techniques that concentrate on a singular objective, MS-TORO highlights target-oriented optimization, which means it focuses on meeting specific goals established by stakeholders instead of solely maximizing or minimizing a function. Furthermore, this approach considers the uncertainties present in complex systems, enhancing the adaptability of the solutions to evolving situations. MS-TORO has

been utilized in numerous fields, such as aircraft rerouting, where it optimizes flight routes by factoring in the preferences of multiple stakeholders, and environmental management, where it strives to balance sustainability, economic, and social goals. By integrating various stakeholder viewpoints and tackling uncertainties, MS-TORO offers a structured and reliable framework for generating practical and broadly accepted solutions in complicated decision-making contexts.

Among the other MCDM tools, the MS-TORO approach distinguishes itself from others through its explicit focus on accommodating diverse stakeholder objectives and incorporating robustness against uncertainties. While conventional MCDM methods, such as the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and the Combined Compromise Solution (CoCoSo), primarily aggregate multiple criteria to rank alternatives, they often assume a unified decision-maker perspective and may not fully address conflicting stakeholder interests or the presence of uncertainty. In contrast, MS-TORO integrates the varying goals of multiple stakeholders directly into the optimization process, ensuring that the derived solutions are not only efficient but also equitable and acceptable to all parties involved. Additionally, by embedding robust optimization techniques, MS-TORO accounts for uncertainties inherent in complex decision-making environments, enhancing the reliability of its solutions under varying conditions. This comprehensive approach makes MS-TORO particularly suitable for scenarios where stakeholder preferences diverge, and decision robustness is critical, offering a more tailored and resilient framework compared to traditional MCDM methods.

3. Methodology

The MS-TORO model being proposed is capable of managing decision-making processes that involve cooperation among various stakeholders, also known as decision-makers, where the related decision criteria are independent. By independence, it means that a decision criterion can only be most accurately evaluated and determined by a specific decision-maker. Other decision-makers for whom a particular decision criterion is not relevant are not regarded as appropriate experts to frame the decision function. For instance, suppose A, B, and C represent the decision criteria in a decision-making process that includes decision-makers D, E, and F. In this scenario, decision criteria A, B, and C align with the interests of decision-makers D, E, and F, respectively. Hence, only decision-maker D is best suited to formulate decision criterion A in relation to the decision problem. Similarly, decision-maker E is the sole individual capable of developing decision criterion B. Decision-maker F focuses solely on achieving decision criterion C in the context of the decision problem. In other words, decision-maker D is solely concerned with decision criterion A and cannot provide insights for either B or C. Likewise, decision-maker E is unable to provide insights on decision criteria A and C, while decision-maker F is restricted to providing insights on C alone and not on A and B.

Other advanced MCDM techniques in the literature are structured in a manner that allows the decision criteria to be assessed by multiple decision-makers in relation to one another, assuming each decision-maker is capable of evaluating each criterion appropriately. These MCDM techniques are only considered suitable when such a scenario is present. However, if a particular criterion is only recognized by a specific decision-maker, then the application of previously established MCDM techniques might fall short. The introduced MS-TORO model effectively addresses decision-making challenges where decision-makers are focused solely on distinct criteria rather than all the criteria available. Additionally, the model can illustrate how the decision criteria, which represent the interests of the decision-makers, are balanced fairly so that, while creating a mutually acceptable collective solution, no criterion is favored or disadvantaged over the others. The deviation metric

further indicates the risk profile of decision-makers and the level of flexibility they can endure while considering the interests of others.

As an additional empirical analysis, qualitative and quantitative data are gathered from restaurant management experts (i.e., manager, chef, and staff) to aid in the analysis. There is a total of eight experts who have been affiliated with a restaurant in the Philippines for one year to over six years. More detailed information about these experts' demographics is shown in Table 2. Furthermore, a fuzzy TOPSIS method is also performed to serve as a validation tool of the capability of the MS-TORO framework over other MCDM tools.

Table 2. Profile of industry experts.

Demographics	Statistics
Gender	Female: 2 Male: 6
Designation	Manager: 1 Chef/Kitchen Staff: 7
Number of years affiliated with the restaurant	Less than 1 year: 2 1–3 years: 2 4–6 years: 1 More than 6 years: 3
Function	Camera and scale logs waste and software analyzes the data
AI tools used in the restaurant	Winnow Vision: 1 Leanpath: 1 Too Good To Go: 2 Kitro: 1 Popmenu: 1 POS: 1 Chefgpt: 1

3.1. The General Form of the MS-TORO Model

In this section, we introduce the proposed MS-TORO model in both its general format and its specific application regarding the challenges of promoting green buildings, selecting suppliers, and rerouting aircraft following departures, which will be used later to illustrate the model. The subsequent discussions derive from a comprehensive explanation found in the work of Ref. [11].

To start, the overall formulation of the proposed MS-TORO model is expressed in Equation (1). The objective function aims to minimize the variation of performance targets, represented by the symbol θ. This variation is quantified within a closed range of 0 to 1. The performance target reflects the value a stakeholder aims to achieve. Specifically, when τ_k, the soft constraint representing stakeholder k's target, is elevated, the value of θ will equal zero, indicating that stakeholders are adopting a more conservative approach towards their objective targets. Conversely, in more stringent scenarios where τ_k is reduced, θ is compelled to approach 1, indicating that stakeholders are more demanding in establishing higher goals. Under deterministic cases of the decision problem, τ_k is represented by the optimal solution (i.e., targets) generated with respect to each stakeholder. Note that the constraint, $c_{ij}x_n \leq \tau_k(1+\theta)$ only holds when the function that represents the interest stakeholders are to be minimized (e.g., cost). Otherwise, the constraint $c_{ij}x_n \geq \tau_k/(1+\theta)$ holds (e.g., profit). The constraint $a_{ij}x_n \geq b_{ij}$ represents all the other system constraints considered in the decision problem. The expression $c_{ij}x_n$ is defined by the objective function which relates to the interest of stakeholders for every parameter c and variable x. The

parameters and n denote the number of variables x. Additionally, a binary constraint can be added as necessary.

Also, note that τ_1 signifies the lowest possible target performance metric that stakeholders may set while τ_0 represents the highest possible target performance metric. The α values relate to the uncertainty levels that may be realized across the range of 0 to 1.

$$\min \theta_{0 \leq \theta \leq 1} \tag{1}$$

subject to:

$$\sum c_{ij} x_j \leq \tau_k (1+\theta) - \qquad for\ 1 \ \leq j \leq n$$

$$\sum c_{ij} x_j \geq \tau_k / (1+\theta) \qquad for\ 1 \leq i \leq k\ and\ 1 \leq j \leq n$$

$$\sum a_{ij} x_j \leq b_i \qquad for\ 1 \leq i \leq k\ and\ 1 \leq j \leq n$$

$$x_n \geq 0$$

$$\tau = \alpha \tau_1 + (1-\alpha)\tau_0$$

3.2. Implementing MS-TORO Approach in Ranking Food Wastes Management AI Technologies

Given that there are k stakeholders, also known as decision-makers, each with distinct decision criteria and performance objectives denoted by τ. Additionally, assume that the decision issue can be represented as a choice problem using a pure integer linear programming approach. This decision problem is started with multiple objective functions while adhering to system constraints. The suggested MS-TORO model aids in the selection of alternatives according to a predefined set of criteria. To specifically formulate the MS-TORO approach according to the context of this paper, the following research design follows the case of ranking food waste management AI technologies:

Step 1: Establish alternative AI technologies for food waste reduction in restaurant management.

Consider a situation where n alternatives are present in the decision-making process, labeled as $\{x_1, x_2, x_3, \ldots, x_n\}$. The goal of the decision-makers is to derive a consolidated solution from the available choices, denoted as x_n. In this particular example, the optimization approach utilizes an integer linear programming model to facilitate a selection-based decision framework. Furthermore, the alternatives considered in this paper include four AI-based technologies (e.g., Winnow Vision, Leanpath, Too Good To Go, Kitro) for food waste reduction in restaurant management.

Step 2: Build the decision criteria system involved in the problem.

The system for decision criteria represents the priorities of decision-makers, typically defined as a target function aimed at either minimizing or maximizing outcomes. The coefficients associated with the decision criteria, c_n, represent the parameters necessary to fulfill a specific interest of the decision-maker. Consider that there are n decision criteria represented as $\{x_1, x_2, x_3, \ldots, x_n\}$. By incorporating the parameters into the decision criteria, the equation can be expressed as $c_n x_n \leq \tau_k (1+\theta)$ for minimization objectives, and/or $c_n x_n \geq \tau_k / (1+\theta)$ for maximization goals. Reflecting these conditions to the context of this paper, the decision criteria considered are as follows: waste reduction, costs, and data accuracy of the AI technology.

Step 3: Set up the direction of decision criteria.

The criteria for the decision specified in the previous step are defined by a right-hand side value of $\leq \tau_k (1+\theta)$ for a target function that aims to minimize, or $\geq \tau_k / (1+\theta)$ for a target function that aims to maximize. Following the decision criteria stated in the previous step, the goals of waste reduction and data accuracy are expected to be maximized while costs are to be minimized.

Step 4: Set up relevant system constraints.

Consider that there are n sets of constraints, where each parameter $\{a_1, a_2, a_3, \ldots, a_n\}$ has an associated right-hand side value denoted as b_n. Additionally, a constraint is applied to enforce binary variables in the form of $x_n \in \{0, 1\}$. The system's constraints can either be expressed as $a_n x_n \leq b_n$ or $a_n x_n \geq b_n$, depending on what is applicable.

Step 5: Set target performance for each decision criterion (optional).

The target performance, τ, can be established analytically by decision-makers as they find appropriate. If this approach is chosen, this step can be omitted. Alternatively, the target can be determined in a more objective way as detailed below:

Step 5.a. Set target performance for each decision criterion.

Suppose that those making decisions strive to either minimize or maximize a particular criterion, which can be expressed as an objective function being min(or max) $c_n x_n$ with the consideration of system constraints. The entire linear programming model designed to produce the optimal value, or the desired target, for each decision criterion can be formulated as shown in Equation (2):

$$\min(\text{or } \max) c_n x_n \tag{2}$$

subject to:

$$\sum a_{ij} x_n \leq b_i \qquad for \quad 1 \leq i \leq k \quad and \quad 1 \leq j \leq n$$

$$\sum a_{ij} x_n \geq b_i \qquad for \quad 1 \leq i \leq k \quad and \quad 1 \leq j \leq n$$

$$x_n \in 0, 1$$

Step 5.b. Run the model and generate results.

A linear programming model solver can be utilized to execute the model and produce the optimal value corresponding to the target performance for each decision-maker. In addition to the target metric, a solution set can also be generated, reflecting the assumed preferences of decision-makers if their own criteria are regarded as the sole factor in the decision process. The model in Step 5.a. can be re-executed for various decision criteria as needed. This means that any decision criterion that necessitates a target can be processed using such a model. In conclusion, a target that aligns with the decision criteria of decision-makers, along with individualized solution sets tailored to their specific criteria, is produced at this stage. These outputs from the model can be employed for further comparative analyses in relation to the aggregated preferences that will be derived from the proposed MS-TORO model.

Step 6: Set objective function subject to the decision criteria and system constraints to form the MS-TORO model.

In this step, the objective function takes on to minimize θ representing the deviation from the target set by decision-makers with respect to the decision criteria. This deviation metric is a member of a closed interval $[0, 1]$. For a decision-maker who seeks to minimize a target performance, a higher value of θ implies a risk profile being more rigid and strict to the achievement of the target. On the other hand, a lower value of θ signifies a more conservative decision-maker with respect to the achievement of the target. For a decision-maker who seeks to maximize a target performance, the value of θ is interpreted in the opposite manner. The complete MS-TORO model can be presented as in Equation (3).

$$\min \theta \tag{3}$$

subject to:

$$c_{ij} x_j \leq \tau_k (1 + \theta) \qquad for\ 1 \leq i \leq k\ and\ 1 \leq j \leq n$$

$$c_{ij}x_j \geq \tau_k/(1+\theta) \qquad for \quad 1 \leq i \leq k \quad and \quad 1 \leq j \leq n$$

$$\sum a_{ij}x_n \leq b_i \qquad for \quad 1 \leq i \leq k \quad and \quad 1 \leq j \leq n$$

$$\sum a_{ij}x_n \geq b_i \qquad for \quad 1 \leq i \leq k \quad and \quad 1 \leq j \leq n$$

$$\tau = \alpha\tau_1 + (1-\alpha)\tau_0$$

$$x_n \in 0, 1$$

$$\theta \in 0, 1$$

Step 7: Run the model and generate results.

A linear programming model solver can be utilized to execute the model. The outputs include both the deviation metric θ and the solution set based on the decision problem. The deviation metric θ indicates how much the targets established by each decision-maker for individual decision criteria can be adjusted to achieve a feasible solution that can also be combined with the criteria of other decision-makers. A θ value that is equal to or nearing 0 signifies an entirely favorable situation, as this indicates that a feasible aggregated solution is reached while fully meeting the targets set by the decision-makers. Conversely, a θ value that is equal to or approaching 1 denotes the highest level of deviation that the model can accommodate while still satisfying the system constraints and delivering feasible solutions.

4. The Case of Food Waste Reduction in Restaurant Management

This section demonstrates a case study on ranking AI technologies for food waste reduction in restaurant management in a developing country, such as the Philippines. To further illustrate the relevance of the proposed MS-TORO model, this framework is run on a MacBook Air computer operating in a macOS Sequoia Version 15.3 under the GAMS Studio 1.19.3 64 bit software environment.

Restaurant management in Cebu City, Philippines, needs to analyze alternative AI technologies for food waste reduction. In this case, four alternative AI technologies, namely, Winnow Vision, Leanpath, Too Good To Go, and Kitro, are considered with the goals of reducing waste, minimizing costs of operation, and increasing data accuracy (see Table 2). Generally, Winnow Vision, Leanpath, Too Good To Go, and Kitro can all be categorized as AI-driven solutions due to their use of artificial intelligence techniques like machine learning, computer vision, and predictive analytics to tackle food waste. Winnow Vision employs computer vision, a fundamental AI technology, to automatically identify and record food items thrown away in commercial kitchens. By positioning a camera above waste bins, the system uses image recognition algorithms to determine the types and amounts of food, improving its accuracy over time through machine learning. In a similar fashion, Leanpath harnesses AI through predictive analytics and data-centric insights. Although it may not overtly utilize AI hardware like cameras, Leanpath gathers data on food waste and applies machine learning to identify patterns, predict trends, and suggest operational modifications to reduce waste. Too Good To Go also utilizes artificial intelligence, especially in demand forecasting, dynamic pricing, and personalizing user experiences. The app connects consumers with businesses that have excess food, employing AI algorithms to optimize the matching process, propose ideal pricing, and enhance the user experience based on behavioral data. Lastly, Kitro combines computer vision and machine learning to monitor and categorize food waste in real time. By analyzing images from a camera placed above a waste bin and integrating data from a built-in scale, Kitro provides comprehensive insights into waste trends, aiding businesses in making data-driven decisions. Each of these technologies effectively utilizes AI to minimize food waste, serving as legitimate examples of AI-driven advancements in the food sustainability arena.

Aside from the goals of reducing waste, minimizing costs, and improving data accuracy, system constraints are also taken into account, as shown in Table 3. This case of food reduction AI technologies analysis is translated into an MS-TORO model shown in the following sections, where the goals and system constraints shown in Tables 3 and 4 are incorporated accordingly.

Table 3. Goals of alternative technology analysis.

Decision Criteria	Winnow Vision	Leanpath	Too Good To Go	Kitro	Target Performance
Waste reduction (in maximum percentage)	50	30	40	60	80
Costs (in dollars annually)	8000	10,000	3600	8000	7000
Data accuracy (in maximum percentage)	75	95	90	90	85

Table 4. Additional system constraints in the technology selection process.

System Constraints	Winnow Vision	Leanpath	Too Good To Go	Kitro	Limit
Availability of resources (in unit costs)	50	30	40	60	50
Implementation time (in number of days)	10	5	3	3	15
Data storage required (in gigabytes)	220	180	100	150	500

5. Model Formulation

The following notations are used to represent the MS-TORO model developed in this paper (Table 5).

Table 5. Notations used in this paper.

Notations	Description
n	AI technologies (n = Winnow Vision, Leanpath, Too Good To Go, Kitro)
k	Decision criteria (k = 1, 2, 3)
x_n	Binary variable representing the selection of an AI technology n
θ	Deviation metric that is continuous in scale from 0 to 1
τ	Target performance of decision criteria k
c_{kn}	Value of decision criteria k per AI technology n

These notations are then plugged into the expanded model formulation shown below, where Equation (4) represents the objective function of minimizing the deviation metric, θ. Constraints (5)–(7) represent the decision criteria, or simply the interest, of stakeholders, including waste reduction, costs, and data accuracy. Note that the right-hand side of Equations (5) and (6) is lesser than or equal to the target performance per decision criteria, k, following the nature of this goal, which is a minimization direction. Constraint (8) restricts the model to select an AI technology, n, that is within the company's available resources. Constraint (9) is attributed to the intended implementation period per AI technology, n. In Constraint (10), the data storage required per technology has to be within the specified limit according to the company. On the other hand, Constraint (11) reflects target performance

corresponding to the third decision criteria on data accuracy, which is considered an uncertain parameter in this paper. This constraint shows the minimum and maximum values of the target performance, τ_3, depending on the uncertainty level, α. Constraint (12) forces the model to select only one AI technology for implementation and Constraint (13) requires x_n to be set as a binary variable. Finally, the deviation metric θ must be within an interval of 0 to 1, as shown in Constraint (14).

$$\min \theta \tag{4}$$

subject to:

$$50x_1 + 30x_2 + 40x_3 + 60x_4 \leq 80(1+\theta) \tag{5}$$

$$8000x_1 + 10000x_2 + 3600x_3 + 8000x_4 \leq 7000(1+\theta) \tag{6}$$

$$75x_1 + 95 + 90x_3 + 90x_4 \geq \frac{\tau_3}{1+\theta} \tag{7}$$

$$50x_1 + 30x_2 + 40x_3 + 60x_4 \leq 50 \tag{8}$$

$$10x_1 + 5x_2 + 3x_3 + 3x_4 \leq 15 \tag{9}$$

$$220x_1 + 180x_2 + 100x_3 + 150x_4 \leq 500 \tag{10}$$

$$\tau_3 = 55\alpha + (1-\alpha)100 \tag{11}$$

$$x_1 + x_2 + x_3 + x_4 = 1 \tag{12}$$

$$x_n \in 0, 1 \tag{13}$$

$$\theta \in 0, 1 \tag{14}$$

6. Model Validation and Discussion

Implementing the model according to its baseline scenario when there is no uncertainty involved, it is clear that the AI technology, Too Good to Go, is selected by the model (see Table 6, column under 0.0 uncertainty level). This means that selecting this AI technology provides the minimum deviation metric while satisfying the system constraints embedded in the model. As a sensitivity analysis, the model is run across different realizations of uncertainties from 0.1 to 1.0, where 1.0 represents absolute uncertainty in the system. The results of this sensitivity analysis are shown in Table 6 from columns 0.1 to 1.0 uncertainty level. It can be noted that whether there is no uncertainty or an absolute uncertainty in the target performance regarding data accuracy, the model selects Too Good To Go as a viable AI technology with respect to the system goals and constraints (i.e., a value of 1 in the columns under each uncertainty level). On the other hand, to enrich the insights generated from this paper, after the model selects Too Good To Go as its prime AI technology alternative, the model is rerun omitting this technology so that a second choice is generated. In this case, Kitro is found to be the next preferred AI technology. This is followed by Winnow Vision and Leanpath.

According to these key results, the MS-TORO framework is able to offer a powerful and adaptable structure for solving complex, multi-objective problems across various domains (e.g., aircraft rerouting, microbusinesses critical failure factors). When applied in contexts such as food waste reduction technologies like Winnow Vision, Leanpath, Too Good To Go, and Kitro, MS-TORO's core strength lies in its ability to balance the often-competing goals of diverse stakeholders while ensuring robust, data-driven solutions. As the framework scales to broader applications, it proves highly valuable in sectors such as healthcare, energy, logistics, and public policy, where decision-making involves navigating trade-offs among actors with differing priorities. For example, in the energy sector, it can balance cost

efficiency for providers, reliability for consumers, and sustainability goals for regulators. In public health, it can guide policy that simultaneously maximizes patient outcomes, minimizes costs, and adheres to regulatory constraints. In other words, MS-TORO proves to be scalable and easily represents any system that allows for real-time optimization based on evolving data and stakeholder feedback. Ultimately, the MS-TORO framework serves not only as a tool for optimization, but as a governance model that facilitates transparent, equitable, and resilient strategies across increasingly interconnected systems.

Table 6. Selection of AI technologies for food waste reduction under uncertainty.

AI Technology	Uncertainty Level											Rank
	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0	
Winnow Vision	0	0	0	0	0	0	0	0	0	0	0	3
Leanpath	0	0	0	0	0	0	0	0	0	0	0	4
Too Good To Go	1	1	1	1	1	1	1	1	1	1	1	1
Kitro	0	0	0	0	0	0	0	0	0	0	0	2

Further Empirical Analysis

To further enrich the context of using AI technologies for food waste reduction in restaurant management, both qualitative and quantitative approaches are employed to generate insights from industry experts. Eight experts who have been affiliated with restaurants in the Philippines and worked for one year to over six years participated in the survey analysis. After the implementation of AI technologies (e.g., Winnow Vision, Too Good To Go, Leanpath, Kitro, Popmenu, POS, Chefgpt) in restaurants, the rate of order processing time has improved to 53%. On average, the time saved per day due to the use of AI tools is more than 40 min. Furthermore, after the introduction of AI to restaurant management, food waste has been observed by 50%, 38%, and 12% of the restaurants to decrease significantly, increase slightly, and not change, respectively. In terms of overall efficiency after implementing AI technologies, restaurants have noted a 46% increase in efficiency and overall satisfaction with AI performance of 78%. Aside from this, AI technologies for food waste reduction have made the jobs of managers, chefs, and kitchen staff easier by 85%. Finally, these experts expressed that by incorporating AI into business operations, companies can deliver quicker services, enhance efficiency, and improve safety, ultimately leading to increased productivity and precision. Automation powered by AI can optimize tasks, decrease preparation time, and provide greater accuracy in decision-making, such as forecasting demand and overseeing inventory. For instance, AI can create recipes based on the ingredients available and dietary preferences, minimizing the time needed for meal preparation. In the realm of inventory management, AI can help avoid overstock situations and monitor product freshness, ensuring items are utilized before they expire. Although the adoption of AI is not yet widespread, gradual implementation in areas such as safety monitoring, workflow enhancement, and inventory management can result in considerable boosts in both productivity and operational efficiency.

To aid in the evaluation of AI technologies for food waste reduction in restaurant management, a fuzzy TOPSIS approach is carried out in this paper with the same model components considered in the MS-TORO framework. The goal of this further empirical analysis is to prove that MS-TORO is indeed better than subjective-based MCDM analysis tools. The fuzzy TOPSIS approach follows the operational framework shown in Figure 1.

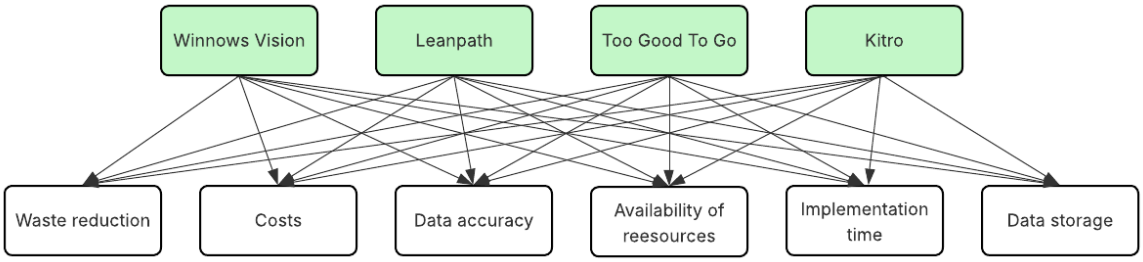


Figure 1. Fuzzy TOPSIS model for evaluating AI technology for food waste reduction.

The fuzzy TOPSIS approach proceeds with the evaluation of AI technologies (i.e., Winnow Vision, Leanpath, Too Good To Go, and Kitro) with respect to the decision criteria (i.e., waste reduction, costs, data accuracy, availability of resources, implementation time, and data storage). A five-point linguistic rating scale from Very Poor to Very Good is used to evaluate the performance of a technology with respect to each decision criterion. This evaluation process is performed by eight experts in the field. For brevity purposes, the details of the fuzzy TOPSIS approach will not be shown in this paper; however, the key result of the implementation is highlighted in Tables 7–13.

Table 7. Evaluation of AI technologies performance with respect to decision criteria according to Expert 1.

AI Technology	Waste Reduction	Costs	Data Accuracy	Availability of Resources	Implementation Time	Data Storage
Winnow Vision	Fair	Fair	Fair	Good	Good	Fair
Leanpath	Fair	Good	Good	Good	Fair	Good
Too Good To Go	Fair	Fair	Fair	Fair	Fair	Fair
Kitro	Fair	Good	Good	Good	Good	Good

Table 8. Fuzzified evaluation of AI technologies with respect to decision criteria according to Expert 1.

AI Technology	Waste Reduction	Costs	Data Accuracy	Availability of Resources	Implementation Time	Data Storage
Winnow Vision	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)
Leanpath	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(5, 7, 9)
Too Good To Go	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)
Kitro	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)

Table 9. Aggregated evaluation of AI technologies according to all experts.

AI Technology	Waste Reduction	Costs	Data Accuracy	Availability of Resources	Implementation Time	Data Storage
Winnow Vision	(3, 6.25, 10)	(3, 6.25, 10)	(3, 6.25, 10)	(3, 6.50, 9)	(3, 6.50, 10)	(3, 6.25, 10)
Leanpath	(3, 6.25, 10)	(3, 6.75, 10)	(3, 6.50, 10)	(3, 6.25, 10)	(3, 6.25, 10)	(3, 6.50, 10)
Too Good To Go	(3, 6.25, 10)	(3, 6.25, 10)	(3, 6.25, 10)	(3, 6.25, 10)	(3, 6.25, 10)	(3, 6.50, 10)
Kitro	(3, 6.25, 10)	(3, 7, 10)	(3, 6.75, 10)	(3, 6.25, 10)	(3, 6.75, 10)	(3, 6.25, 10)

Table 10. Normalized fuzzy decision matrix.

AI Technology	Waste Reduction	Costs	Data Accuracy	Availability of Resources	Implementation Time	Data Storage
Winnow Vision	(0.30, 0.48, 1)	(0.30, 0.48, 1)	(0.30, 0.63, 1)	(0.33, 0.46, 1)	(0.3, 0.46, 1)	(0.30, 0.48, 1)
Leanpath	(0.30, 0.48, 1)	(0.30, 0.44, 1)	(0.3, 0.65, 1)	(0.30, 0.48, 1)	(0.30, 0.48, 1)	(0.3, 0.46, 1)
Too Good To Go	(0.30, 0.48, 1)	(0.30, 0.48, 1)	(0.3, 0.63, 1)	(0.30, 0.48, 1)	(0.30, 0.48, 1)	(0.3, 0.46, 1)
Kitro	(0.30, 0.48, 1)	(0.30, 0.423, 1)	(0.3, 0.68, 1)	(0.30, 0.48, 1)	(0.3, 0.44, 1)	(0.30, 0.48, 1)

Table 11. Weighted normalized fuzzy decision matrix.

AI Technology	Waste Reduction	Costs	Data Accuracy	Availability of Resources	Implementation Time	Data Storage
Winnow Vision	(2.10, 4.32, 10)	(1.50, 3.36, 9)	(0, 0.63, 3)	(0, 0.46, 3)	(0.30, 1.38, 5)	(0, 0.48, 3)
Leanpath	(2.10, 4.32, 10)	(1.50, 3.11, 9)	(0, 0.65, 3)	(0, 0.48, 3)	(0.30, 1.44, 5)	(0, 0.46, 3)
Too Good To Go	(2.10, 4.32, 10)	(1.50, 3.36, 9)	(0, 0.63, 3)	(0, 0.48, 3)	(0.30, 1.44, 5)	(0, 0.46, 3)
Kitro	(2.10, 4.32, 10)	(1.50, 3, 9)	(0, 0.68, 3)	(0, 0.48, 3)	(0.30, 1.33, 5)	(0, 0.48, 3)
A+	(2.10, 4.32, 10)	(1.50, 3.36, 9)	(0, 0.68, 3)	(0, 0.48, 3)	(0.30, 1.44, 5)	(0, 0.48, 3)
A-	(2.10, 4.32, 10)	(1.50, 3, 9)	(0, 0.63, 3)	(0, 0.46, 3)	(0.30, 1.33, 5)	(0, 0.461, 3)

Table 12. Distance of Winnow Vision to the fuzzy positive and negative ideal solutions.

AI Technology	Waste Reduction	Costs	Data Accuracy	Availability of Resources	Implementation Time	Data Storage
d+	0.0000	0.0000	0.029	0.0107	0.032	0.0000
d−	0.0000	0.2080	0.0000	0.0000	0.0300	0.0110

Table 13. Closeness coefficient and rank of AI technologies.

AI Technology	d+	d−	Closeness Coefficient	Rank
Winnow Vision	0.072	0.248	0.776	2
Leanpath	0.169	0.151	0.472	3
Too Good To Go	0.040	0.280	0.876	1
Kitro	0.269	0.050	0.157	4

The fuzzy TOPSIS method begins with the evaluation of AI technologies with respect to the decision criteria carried out by experts separately. The alternative AI technologies considered in this paper include Winnow Vision, Leanpath, Too Good To Go, and Kitro, while the decision criteria cover waste reduction, costs, data accuracy, availability of resources, implementation time, and data storage. Note that the linguistic scale rating follows the fuzzy TOPSIS rating shown in Table 14. Table 7 shows a sample evaluation performed by Expert 1. For brevity purposes, the evaluation of the remaining seven experts is not shown. Then, this linguistic evaluation is converted to its fuzzy number counterpart, as shown in Table 8. Considering that each expert evaluation produces its own fuzzy response, these data are aggregated into a singular metric, shown in Table 9. The next step involves the normalization of the fuzzy decision matrix shown in Table 10. This matrix is then used to compute the weighted normalized fuzzy decision matrix presented in Table 11. After generating the normalized fuzzy decision matrix, the distances from the positive ideal solution (d+) and negative ideal solution (d−) are calculated for each alternative. Table 12 shows the distance of alternative 1, Winnow Vision, to the positive and negative

ideal solutions. Completing the computation for each alternative, Table 13 summarizes the distances to the positive and negative ideal solutions as well as its closeness coefficient and ranking. The higher the closeness coefficient, the better the preference.

Table 14. Linguistic scale rating.

Linguistic Rating	Fuzzy Numbers
Very poor	(0, 1, 3)
Poor	(1, 3, 5)
Fair	(3, 5, 7)
Good	(5, 7, 9)
Very good	(7, 9, 10)

According to the fuzzy TOPSIS method, the ranking of preference is as follows: First, Too Good To Go; second, Winnow Vision; third, Leanpath; and fourth, Kitro. As a recall, note that the MS-TORO framework has a ranking of the following (see Table 15 and Figure 2). It is interesting to note that regardless of the approach, Too Good To Go emerged as the most preferred AI technology among experts and system model components. However, it is important to highlight that the difference in rankings between the MS-TORO and fuzzy TOPSIS approaches stems from their distinct methodologies and priorities. MS-TORO framework explicitly models and balances the goals of multiple stakeholders while accounting for uncertainty, trade-offs, and performance variability. This allows solutions like Kitro to rank higher if they better align with specific stakeholder-defined targets, such as regulatory compliance, sustainability impact, or scalability, even if they are not the top performer across all general criteria. In contrast, Fuzzy TOPSIS focuses on ranking alternatives based on their overall closeness to an ideal solution, using fuzzy logic to handle imprecise inputs and averaging across weighted criteria. As a result, solutions like Winnow and Leanpath may rank higher under TOPSIS due to consistent performance across broadly defined attributes, even if they fall short of certain stakeholder-specific goals. This explains why Kitro ranks higher in MS-TORO but lower in fuzzy TOPSIS—the former emphasizes targeted robustness and stakeholder alignment, while the latter emphasizes aggregated preference and proximity to an ideal.

Table 15. Ranking of AI technologies according to MS-TORO and fuzzy TOPSIS.

AI Technology	MS-TORO Ranking	Fuzzy TOPSIS Ranking
Winnow Vision	3	2
Leanpath	4	3
Too Good To Go	1	1
Kitro	2	4

Finally, the results validate the strength of the MS-TORO framework by demonstrating its ability to capture nuanced, stakeholder-specific priorities that conventional MCDM methods like fuzzy TOPSIS might overlook. The fact that Kitro ranks higher in MS-TORO, despite being lower in the fuzzy TOPSIS ranking, validates the MS-TORO framework's core advantage: it does not simply seek a one-size-fits-all "best" option but instead identifies solutions that best meet the specific goals and tolerances of diverse stakeholders under real-world uncertainty. This tailored decision-making is particularly valuable in complex environments like food waste management, where different actors—such as corporate decision-makers, sustainability officers, kitchen staff, and regulators—may have conflicting

priorities. MS-TORO's robustness ensures that the selected solution is resilient across a range of scenarios, making it more actionable and reliable in practice. By surfacing a solution like Kitro that might be undervalued by purely aggregate or fuzzy-ranking methods, MS-TORO proves its practical relevance and strategic depth, especially for decisions that involve multiple trade-offs and stakeholder engagement.

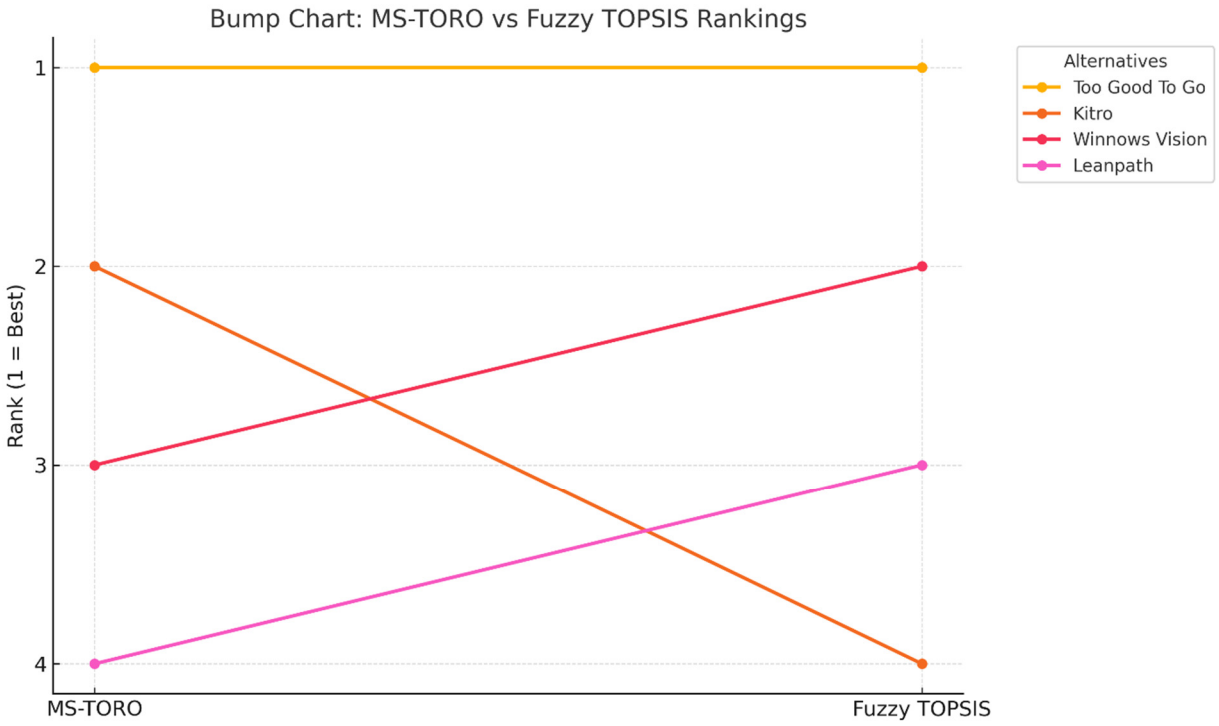


Figure 2. Ranking of AI technologies generated from MS-TORO framework and fuzzy TOPSIS approach.

7. Managerial Implications

Following the potential of implementing AI technologies in reducing food waste across various settings, this paper analyzed four prominent technologies according to the case of restaurant operations in the Philippines. The MS-TORO approach generated key results in Table 6, which can be used to point out significant insights for restaurant managers to consider. For one, the MS-TORO approach favored Too Good To Go in all cases of uncertainties, with a deviation metric ranging from 0.0000 to 0.1111. Note that the deviation metric indicates the level of adjustment that the goals must be set in order to satisfy the other goals. With the remaining AI technologies, the MS-TORO approach is also able to rank the preferences of managers according to the goals and system constraints. Such ranking includes Kitro, Winnow Vision, and Leanpath, in order of preference next to Too Good To Go.

In addition to the top-ranked option, the research creates a preference hierarchy among the other AI technologies: Kitro, Winnow Vision, and Leanpath, respectively. This ranking furnishes managers with a clear decision-making framework when exploring alternative options. The established hierarchy suggests that Kitro may be the most flexible AI-based option following Too Good To Go, whereas Winnow Vision and Leanpath could require more extensive operational adjustments to fit within restaurant limitations and objectives. From a managerial viewpoint, these findings highlight the necessity of assessing AI solutions not merely based on their technological features but also considering their adaptability to specific restaurant challenges such as budget limitations, data storage capacities, and feasibility of implementation. Managers should also regard the deviation

metric as a crucial performance measure, given that lower deviations indicate a smoother integration of technology with existing systems. Moreover, although Too Good To Go stands out as the optimal choice, decision-makers should evaluate their particular operational goals to determine if the potential trade-offs in adopting other technologies are in concert with their restaurant's long-term sustainability and efficiency aspirations.

Research Limitations and Future Research

This paper is able to prioritize AI technologies for food waste reduction in restaurant management. However, the analysis is limited only to the AI technologies evaluated under the system interests and constraints given. Furthermore, the approach is inherently complex, requiring sophisticated mathematical modeling to integrate diverse stakeholder objectives, performance criteria, and uncertainty factors. This complexity can make the method time-consuming to implement and challenging for organizations lacking technical expertise. Additionally, the MS-TORO framework is data-intensive, often requiring detailed and sometimes hard-to-obtain information, such as scenario probabilities and stakeholder-specific performance targets. While it accommodates multiple stakeholder perspectives, it does not automatically resolve conflicts among them, and balancing competing goals can be politically or ethically sensitive. The computational demands of robust optimization can also be significant, especially for large-scale problems with many variables and constraints.

8. Conclusions

While this paper is the first to analyze the ranking of AI-based technologies used in food waste reduction for restaurant management, several interesting insights can be generated according to the key results of the MS-TORO approach. First, the study reaffirms the significance of AI in food waste management and advocates for restaurant managers to embrace a data-informed strategy in selecting the most suitable and practical technology for their operations. Second, for developing nations like the Philippines, the ranking of preferences is essential due to the need to cut down on food waste, which is vital for economic and environmental sustainability. Given that Too Good To Go consistently ranks as the top AI technology, embracing this solution offers a budget-friendly and attainable option for restaurants in settings with limited resources. Since this platform emphasizes the redistribution of surplus food rather than depending on advanced infrastructure, it is more suitable for developing countries where financial and technical limitations may hinder the adoption of more sophisticated AI-driven waste monitoring systems.

Moreover, the rankings of alternative technologies—Kitro, Winnow Vision, and Leanpath—indicate that while AI-based food waste tracking can be advantageous, its practicality in the Philippines might rely on elements such as digital infrastructure, data storage capabilities, and restaurant size. Numerous restaurants, particularly small and medium-sized enterprises (SMEs), might face challenges related to the high initial investment and technical demands linked to advanced AI solutions. This illustrates the necessity for government support, subsidies, or public–private collaborations to enable the integration of AI in managing food waste. In addition, the research highlights the necessity of tailoring AI-driven waste reduction strategies to local conditions. In the Philippines, where food security is an urgent matter, merging food waste technologies with community-based initiatives, food banks, and sustainability projects could amplify their effectiveness. Policies encouraging food donations, tax benefits for waste reduction technologies, and digital literacy initiatives can further promote AI adoption and make food waste mitigation more inclusive and scalable.

With respect to the utilization of MS-TORO framework as an approach to prioritize AI technologies for food waste reduction in restaurants, it is important to note the scalability

and repeatability of the framework across other similar domains. That is, its adaptability in different applications—from managing food waste to shaping energy policy and enhancing public health—highlights its potential as both a powerful optimization tool and a strategic governance framework. By facilitating transparent, flexible, and data-driven solutions, MS-TORO provides a solid basis for promoting resilience and fairness in systems where conflicting objectives need to be effectively aligned. Not to mention that the MS-TORO framework further showcases a significant ability to tackle intricate, multi-objective issues across various sectors by incorporating real-time data and stakeholder interactions into its decision-making model.

Overall, the conclusions stress that while AI presents promising opportunities for managing food waste, developing countries need to confront economic and infrastructural challenges to fully realize its advantages. A strategic approach that balances cost-effectiveness, accessibility, and long-term sustainability will be crucial for successful implementation in the Philippines and similar economies.

Funding: This research received no external funding.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: There are no conflicts of interest in this paper.

Declarations: The author has read and agreed to the published version of the manuscript.

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