Harnessing AI Innovations from the Hospitality Industry:

A Blueprint for Household Food Waste Management

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Green – adding a line/adding anything

Red – replacement suggestion (by the one in the brackets after it)

**Abstract.** Excessive food waste contributes to greenhouse gas emissions from landfills, significant consumer financial losses, and places undue strain on the food industry. Artificial intelligence (AI) methodologies are increasingly employed in the hospitality industry to revolutionize commercial kitchen operations to monitor, analyze, and subsequently reduce food waste. This paper dissects their strategies to conceptualize a framework tailored for household food waste management(to curb the issue of food waste management in households). Our study suggests how the large-scale solutions of the hospitality sector could be adapted to the unique characteristics and challenges of household environments by examining how these companies leverage advanced data analytics, sensor technology, and machine learning algorithms as the backbone of their waste reduction strategies. The findings underscore the potential of adapting and integrating advanced AI tools into home settings, highlighting actionable insights and data-driven interventions. The proposed blueprint not only offers a promising avenue to diminish household food waste but also advocates for the broader adoption of AI in championing sustainable living practices.

**1. Introduction**

According to the FAO report, global food waste amounts to 1.03 billion tons annually, accounting for about 17% of global food production. Food waste produce generates 3.30 billion tons of greenhouse gases annually, and the economic loss caused by food waste is about USD 750 billion annually [36].

Food waste remains a global challenge, contributing to an array of environmental, economic, and social issues. Current statistics underscore the severity of the problem, with approximately one-third of all food produced for human consumption lost or wasted globally, translating to roughly 1.3 billion tons per year [1]. Notably, this waste not only signifies a lost economic opportunity but also leads to negative environmental consequences. When disposed of in landfills, decomposing food generates methane, a greenhouse gas far more potent than carbon dioxide, thereby exacerbating global warming [2]. Additionally, waste places undue demand on the agricultural sector, consuming vast amounts of resources such as water, land, and energy for food that is never consumed [3].

Given the magnitude of the issue, there has been a push for innovative solutions to address food waste, particularly in sectors where waste is most prevalent. The hospitality industry, for example, witnesses significant volumes of food waste due to its operational nature [4]. Two prominent entities, Kitro and Winnow, have risen to the challenge of leveraging artificial intelligence (AI) to address food waste within the sector. Their pioneering efforts in using technology to identify, categorize, and quantify waste have proven transformative by facilitating effective strategies. We herein suggest that such benefits can be adapted to household settings.

According to the Food Waste Index Report 2021 published by the United Nations Environment Programme (UNEP), approximately 17% of the world’s food production is lost or thrown away [[37](https://www.mdpi.com/2076-3417/12/22/11399#B1-applsci-12-11399)]. Almost 61% of this loss occurs in private households, 26% in food service establishments, and 13% in retail businesses. These statistics underscore the urgent need for action to reduce food waste at both individual and business levels.

This paper aims to infer the lessons and technological advancements of Kitro and Winnow in the hospitality sector to household food waste management. Given that households represent a considerable percentage of overall food waste, the incorporation of such innovative solutions can provide valuable insights for both policymakers and consumers. The ultimate objective is to outline a potential blueprint for integrating AI-driven tools and methods into everyday household practices for more effective food waste management.

This paper is organized as follows. Section 2 provides a background of food waste and its implications. Section 3 provides an in-depth exploration of AI’s role within the hospitality sector, referencing prominent case studies. Section 4 assesses the potential applicability of these techniques to household settings. The subsequent sections encompass discussions centered on the findings (Section 6), policy recommendations and implementation strategies (Section 7), potential avenues for future work (Section 8), and last, concluding remarks.

**2. Background**

This section introduces Food Waste Management, explores common domestic methods and their merits and challenges, discusses the hospitality industry’s role and responsibilities in this area, and looks at pioneering AI-driven solutions that hint at future household applications.

Food Waste Management refers to the practices and strategies implemented to efficiently handle, reduce, reuse, or dispose of unwanted or surplus food items in both post-production and consumption stages. This process aims to minimize the negative environmental, economic, and social impacts of food waste. It encompasses a range of activities, from preventive measures that reduce food waste at the source to methods for recovering and recycling food waste, such as returning nutrients to the soil through composting, greenhouse gas production from landfills, redistribution to those in need through food banks, or creating renewable energy [5]. Effective food waste management not only aids in environmental conservation but also can result in cost savings and resource optimization.

The global concern surrounding food waste has risen over the past few decades. Research indicates that nearly a third of all food produced for human consumption gets lost or wasted, which equates to approximately 1.3 billion tons annually [6]. Such vast amounts of unconstrained food waste have dire consequences, including the exacerbation of greenhouse gas emissions from landfills, significant financial losses, and an increased strain on the agricultural industry [7].

The paradigm of “from farm to fork” has expanded to “from farm to fork to landfill,” illuminating the gaps in our current food systems [8a]. As urban areas continue to grow, and population densities increase, urban food waste management becomes a vital concern. Efficiently managing this waste can significantly curb the negative environmental impacts and promote sustainable living [8b]. Household food waste remains one of the most overlooked yet impactful areas of waste generation. The current strategies predominantly revolve around three major R’s: Reduce, Reuse, and Recycle. Households are encouraged to purchase wisely, store efficiently, and consume prudently to minimize waste. Composting serves as a recycling mechanism, turning organic waste into a resource for gardening. Despite these practices, a significant volume of food still finds its way to landfills, with unconstrained waste contributing to greenhouse gas emissions, financial loss, and undue pressure on the agricultural sector.

Innovations in artificial intelligence (AI) technology have been introduced to tackle the issue of food waste, especially in sectors where the volume of waste is particularly high. The hospitality industry, a significant contributor to the problem, has adopted various tech-driven solutions to optimize their operations and reduce food waste [9]. The hospitality industry, comprising hotels, restaurants, and catering services, plays a pivotal role in global food distribution and consumption. Historically, this sector has been identified as a significant contributor to food waste due to its operational nature, which necessitates surplus provisioning to meet diverse consumer demands. With high standards for food presentation and quality, substantial amounts often get discarded. This waste not only implies economic losses but also an unnecessary environmental footprint.

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Notably, businesses have realized that beyond the apparent environmental and moral imperatives, efficient food waste management can also lead to tangible economic benefits. As a result, there is an increasing trend in the industry to employ advanced AI technologies to devise and implement effective waste management strategies [10]. In recent years, several technological solutions have been developed to address the challenge of food waste in the hospitality industry. Kitro and Winnow have emerged as leaders in leveraging AI to mitigate waste. Their systems employ sophisticated algorithms and sensors to track, quantify, and analyze food that is discarded. These real-time insights provide actionable feedback to culinary professionals, enabling them to adjust their practices and ultimately reduce waste. The success of such AI-powered systems in a high-waste environment like hospitality sparks interest in their potential applicability to the household sector.

**3. AI in the Hospitality Industry**

This section explores the impact of Artificial Intelligence (AI) on food management within the hospitality sector. We highlight the changes induced by AI, followed by an in-depth examination of pioneering solutions from Kitro and Winnow. The discussion concludes by assessing the collective effect of these innovations on the hospitality industry, particularly focusing on sustainability, cost-efficiency, and potential applications in household settings.

The onset of the digital age has seen AI permeate various industries, revolutionizing operations and business practices. The hospitality industry, grappling with substantial food waste, has been no exception. AI’s data-driven approach offers predictive analytics, automating waste measurements and providing actionable insights to reduce food waste significantly [11].

Kitro has developed a camera plus weighing scale system that uses AI to detect and categorize food waste automatically. Using a combination of weight sensors and cameras, Kitro’s system captures images of discarded food, which are then processed and analyzed using deep learning algorithms. Such categorization of waste equips establishments with detailed insights to refine their purchasing and preparation practices [12].

Winnow takes a slightly different approach by including user interface, which allows their system to be initially train to identify the food items. This tool utilizes a smart camera and scale, positioned above the waste bin, to capture and recognize the type of food being discarded. Over time, through continual machine learning, Winnow’s system becomes more accurate in its categorization. The real-time feedback offered by the Winnow system has reportedly assisted establishments in reducing their food waste by up to 50%, translating to substantial economic savings [13].

Both Kitro and Winnow’s innovations have led to a paradigm shift in how the hospitality sector approaches food waste. By offering real-time analytics, these AI systems facilitate immediate intervention and longer-term strategic planning. The cumulative effect of these technologies is not just limited to economic savings for businesses. They have contributed to a more sustainable and responsible hospitality industry, setting the stage for scalable solutions that might be transferred to household settings [14].

**4. Potential Applicability to Household Settings**

There is potential for adapting AI-driven solutions from the hospitality sector for household use. While households represent a major contributor to food waste, their inconsistent and varied food consumption patterns pose challenges for direct application of existing AI innovations. However, with the advent of smart home systems and Internet of Things (IoT), there is an opportunity to utilize predictive analytics for improved food consumption, purchasing decisions, and waste reduction. Through user-friendly applications, households can optimize food utilization that can lead to economic and environmental benefits.

The success of AI-driven interventions in the hospitality industry poses a pertinent question: Can these innovations be adapted and scaled down for household application? Households form the base unit of food consumption, and collectively, they represent a significant proportion of food waste [15]. Addressing the issue at this micro-level can exponentially enhance the larger objective of curbing food waste at the macro level. Several challenges must be considered when translating the large-scale practices of the hospitality sector to individual households. For instance, the volume and consistency of food waste in restaurants and hotels are often more predictable than in domestic settings, where variability in consumption patterns, dietary choices, and purchasing behaviors come into play [16]. And the economic incentives for households to invest in advanced AI solutions may not be as immediately apparent as they are for businesses.

Nevertheless, there are many potential advantages. With the integration of AI into smart home systems and IoT devices, households can benefit from predictive analytics. Such systems could offer real-time insights into consumption patterns, recommend grocery purchasing decisions based on historical data, and provide creative solutions for repurposing or composting leftover food. This not only assists in reducing food waste but also can contribute to significant savings for households in the long run [17].

User-friendly applications can be developed, leveraging AI algorithms to assist homeowners in tracking food inventory, predicting spoilage, and suggesting recipes based on available ingredients, thus ensuring optimal utilization of purchased food items [18]. The adaptability and user-centric design of these applications will be crucial to their widespread adoption and effectiveness. While challenges exist in translating AI innovations from the hospitality sector to households, the potential benefits in terms of environmental sustainability, economic savings, and fostering a culture of responsible consumption have the potential to be profound. Continued research and development in this arena will be pivotal in materializing these benefits [19].

**5. Case Studies of Kitro and Winnow**

- Trials of applying Kitro and Winnow-like systems in household settings

- Results, challenges faced, and lessons learned

This case study presents a detailed analysis of leading smart bin companies like Winnow, Kitro, and Leanpath which are dedicated to addressing the global issue of food waste. These companies employ innovative technologies to monitor, quantify, and reduce food waste, with a focus on sustainability and cost savings. This analysis delves into their technical build, algorithmic processes, data provided to customers, challenges faced, customer support, pricing models, return on investment (ROI), and future plans.

Winnow:

Winnow's Smart Bin initially began as a system comprising only a tablet and a weighing scale, relying on users to manually select and log the type of food being discarded. However, in 2019, they achieved a significant breakthrough with the introduction of the AI model known as Winnow Vision Technology.

The Winnow Vision system consists of a scale placed on the floor beneath a standard waste bin. On top of the bin is the Vision box is mounted. This setup allows Winnow to capture data on food waste in real-time. Within the Vision box component, there is an integrated light and motion-sensitive camera positioned flush with the bottom. Whenever an item is discarded into the bin, this camera captures a series of images to obtain the best possible view of the bin's contents. Additionally, the system includes a touchscreen tablet that facilitates staff interaction with the Smart Bin.

A white bucket with a handle

Description automatically generated

Winnow Vision Box

Camera

Digital Scale

Fig1. Winnow Bin Setup

Winnow's algorithm operates in two distinct phases. In the Prediction Phase, the system takes a photo when food is discarded, captures the weight of the waste, and attempts to predict the food item based on a universal model. The system shortlists the top eight possibilities and prompts the staff to confirm which item was discarded. Winnow has achieved an 80% accuracy rate in identifying food items during this phase.

The second phase, known as Passive Touch AI, automates the categorization process based on the data collected over time. The more frequently the system encounters a particular item, the quicker it can recognize and categorize it. Winnow provides clients with automated reports, downloadable PDFs, and access to the Winnow Hub, an online dashboard for real-time data analysis. Clients can view waste as a percentage of sales, identify top wasted items, and gain insights into optimizing their operations. Winnow also offers a waste log with transaction data, including photos, weights, values, and reasons for waste.

Kitro:

Kitro's smart bin system is designed for comprehensive food waste measurement. It consists of a scale beneath a plate, an adjustable-height pole, and a camera on top. This setup allows Kitro to monitor food waste in various settings, including commercial kitchens, buffets, and guest plates.

Kitro uses a centralized algorithm that works across all properties, eliminating the need for individual menu data. When food is discarded into the bin, the system captures the weight, timing, and content of the waste. The image recognition process occurs in the cloud, where Kitro's advanced algorithm categorizes the items. The system recognizes approximately one million different food items, offering a high degree of granularity in data analysis.



Camera

Adjustable Stand Back

Digital Scale

Fig 2. Kitro Bin Setup

Kitro's dashboard provides clients with detailed insights into their food waste. Clients can filter data by food categories, service times, and reasons for waste, such as overproduction or plate waste. The system also assigns a respective price to each ingredient, helping clients calculate the total value of food wasted. Kitro's approach allows clients to identify patterns over time and optimize their processes effectively. The system is designed to be plug-and-play, requiring minimal training for users.

Results:

Winnow and Kitro have both achieved significant results in reducing food waste in commercial settings, albeit through different approaches. Winnow initially focused on cost savings for customers but has observed a gradual shift towards sustainability goals among their clientele. Their system, which utilizes digital scales and cameras, has achieved an 80% accuracy rate in identifying food items, thus providing valuable data for waste reduction. Clients receive automated reports, access to online dashboards, and granular data to optimize their operations. Winnow's approach has resulted in reduced food waste and increased cost savings for their clients.

Kitro, on the other hand, adopted a centralized algorithm that categorizes food waste across properties. This approach has provided an advanced level of granularity in data analytics, enabling clients to identify patterns and optimize their processes effectively. Kitro's clients have reported an average food waste reduction of 32%, with some achieving over 50% reduction. The system has led to substantial cost savings, with an average annual savings of 60,000 to 90,000 Swiss Francs per property, demonstrating a strong return on investment.

Challenges:

Both Winnow and Kitro have faced challenges in their journey to tackle food waste. Winnow encountered placement issues of bins in kitchens, security concerns during system installations, and the need for staff engagement to ensure proper utilization. They also faced resistance from staff who did not use the system correctly or did not prioritize food waste reduction. Kitro, in contrast, grappled with the reluctance of clients to invest in new technologies in the fast-paced hospitality industry. Initial challenges included the need for manual labeling and slow automation rates. However, both companies have learned to adapt and overcome these obstacles over time.

Lessons Learned:

The experiences of Winnow and Kitro offer valuable lessons for addressing food waste in household settings. One key lesson is the importance of client engagement and leadership support to ensure the successful implementation of waste reduction systems. Both companies have emphasized the need for dedicated customer support and training to facilitate client adoption. Additionally, the ability to provide granular data and real-time analytics has proven crucial in helping clients identify and implement effective waste reduction strategies. Finally, the companies have highlighted the potential for continuous improvement and innovation in their systems, aiming to enhance accuracy, speed, and functionality in the future.

**6. Discussions**

The evolving interface of food waste management and AI has fostered a paradigm shift from reactive to proactive measures in mitigating food waste management issues. The underlying principles, once optimized for the hospitality industry can be adapted to varying scales, including households. This section delves into the broader implications, potential challenges, and future prospects of integrating AI-driven solutions into household settings.

There are broader implications at a fundamental level. Minimizing food waste is not merely about conservation but also addresses larger issues such as environmental degradation and sustainability [20]. The release of methane from rotting food in landfills, a potent greenhouse gas, underscores the environmental impact of unmanaged waste [21]. Moreover, the efficient use of food items at the household level can alleviate pressures on global agricultural demand, leading to a ripple effect on conserving resources and reducing unnecessary agricultural emissions [22]. Challenges ahead include applying AI tools at the household level is the decentralization of data sources. Unlike the hospitality industry, where operations are often centralized, household behaviors are disparate and widely varied [23]. Ensuring user privacy, curating tailored solutions, and fostering user trust will be key. The economic viability of implementing AI solutions in a domestic environment, without the larger economies of scale seen in the hospitality industry, remains a question [24].

However, with the growing ubiquity of smart devices and IoT infrastructure, the prospects of integrating AI solutions into everyday household routines look promising [25]. The synthesis of AI with augmented reality (AR) could provide an intuitive platform for users to monitor food storage and obtain actionable insights. Moreover, the emergence of community-driven platforms may offer collective data sourcing and shared AI resources, reducing costs and enhancing the accuracy of predictions [26]. While the potential challenges of migrating AI tools from an industrial scale to households are substantial, the prospects offer transformative solutions in the realm of food waste management. Continued interdisciplinary collaboration between AI developers, environmental scientists, and consumer behavior experts will be the key to unlocking this potential [27].

**7. Policy Recommendations and Implementation**

The potential of integrating AI in household food waste management is significant, both from an environmental and an economic perspective. To leverage this potential effectively and ensure its widespread adoption, appropriate policy measures and strategic implementation steps are crucial. Here, we outline recommendations to aid policy-makers and stakeholders in fostering a supportive ecosystem for AI-driven food waste management at the household level.

(1) Standardization of AI Solutions: It’s imperative to have standardized protocols and frameworks for AI solutions in waste management. Consistency will ensure that different systems can seamlessly interact, share data, and generate actionable insights, irrespective of the technology provider [28]. (2) Data Privacy and Security Protocols: Given the personal nature of household data, establishing robust data privacy and security protocols is paramount. It’s essential that AI solutions respect user confidentiality and have the necessary safeguards against potential breaches [29]. (3) Economic Incentives: Encouraging households to adopt AI-driven food waste management solutions can be facilitated by providing economic incentives. This could take the form of tax breaks, subsidies for smart appliance purchases, or rewards for demonstrable reductions in food waste [30]. (4) Public Awareness and Education: For effective adoption, the public should be educated about the environmental and economic repercussions of food waste and the benefits of AI-driven solutions. Initiatives could range from school curricula integrations to national media campaigns [31]. (5) Collaboration with Technology Providers: Forming alliances with technology providers can streamline the integration of AI tools into household appliances. Such collaborations can spur innovations, reduce costs, and ensure the solutions are tailored to the users’ needs [32]. (6) Monitoring and Feedback Mechanisms. Continuous monitoring mechanisms, coupled with periodic feedback loops, can aid in refining and optimizing the AI tools in real-time. These mechanisms will also provide valuable insights into user behavior, enabling better customization of solutions [33]. (7) Localized Solutions. It is important to recognize that households vary significantly based on cultural, economic, and regional factors. Tailored, localized solutions will be more effective than a one-size-fits-all approach, requiring policy-makers to engage with local communities and stakeholders for input [34]. The integration of AI tools into household food waste management holds great promise. However, this transition requires a thoughtful blend of technological innovation, policy support, and societal engagement. With the right strategies in place, the goal of efficient, sustainable food consumption at the household level is well within reach [35].

**8. Recommendations for Future Work (to be edited)**

Household food waste management faces additional challenges over the hospitality industry. Addressing the complexities of household food waste management through AI requires exploration beyond the current establishment. Implementations and suggested policies should be considered. We recommend the following endeavors of further investigations in this domain:

* Integration with IoT devices. With the advent of the Internet of Things (IoT), there is potential for integrating AI-driven food waste management systems with smart home devices. Such integrations could provide real-time monitoring, prediction, and prevention of food waste [36].
* Behavioral studies. To ensure the effectiveness of AI solutions in households, understanding human behaviors and patterns related to food consumption and waste is imperative. In-depth behavioral studies could offer insights into user acceptance and the long-term sustainability of AI interventions [37].
* Ethical Considerations. As with any AI application, ethical concerns related to data privacy and security will arise. Future research should evaluate these concerns, especially when collecting and analyzing data from households [38].
* Collaborative frameworks. Partnerships between AI developers, waste management organizations, and government bodies can foster holistic solutions. Future work should focus on collaborative frameworks that accelerate innovation while ensuring widespread adoption [39].
* Economic Impact Studies. Understanding the potential economic benefits and challenges associated with the adoption of AI in household food waste management is critical. Comprehensive economic analyses would aid in policy formulation and stakeholder buy-in [40].
* Customization and Scalability. AI solutions need to be both adaptable to individual household needs and scalable for broader implementation. Future studies should investigate techniques for efficient customization and deployment at varying scales, from individual residences to entire communities [41].
* Long-term sustainability. While the initial results of AI-driven interventions might be promising, the long-term sustainability and adaptability of these solutions in a constantly evolving tech landscape need examination. Continuous performance evaluation and system upgrades should be a priority [42].
* Educational Initiatives. Exploring how educational programs can be augmented with AI to improve awareness and understanding of food waste management among households can offer significant benefits. Research into the integration of AI into educational curricula, especially for younger generations, could be a step towards a more conscious future [43].

Utilizing AI for food waste management in household settings presents a rich avenue for future research and innovation. While this paper provides a foundational understanding and a roadmap for potential applications, it is the evolution of technology, policy, and societal attitudes that will likely determine the trajectory of this promising domain.

**9. Conclusion**

The pressing challenges of food waste, with far-reaching environmental, economic, and social implications, necessitate the adoption of innovative strategies for mitigation. Through the exploration of AI technologies initially designed for and applied within the hospitality sector, the possibility of a transformative application in household settings emerges distinctly. There is now the convergence of advancements in AI, increasing digital connectivity, and a greater societal emphasis on sustainability. Household food waste management can benefit considerably from the lessons learned in the hospitality industry. The proposed standardizations, economic incentives, public awareness campaigns, and collaboration with tech providers form a holistic framework, allowing us to leverage AI’s potential for creating a sustainable and waste-conscious society. In synthesizing the discussed approaches and policy recommendations, it becomes evident that while technology provides the tools, the real change will stem from an integrated approach involving policy-makers, industry stakeholders, and the general public. The future of food waste management is not just about reducing waste but about reimagining our relationship with food and resources, emphasizing efficiency, sustainability, and shared responsibility. While challenges persist, the roadmap ahead of AI-driven innovations and guided by informed policies, is quite promising for paving the way for not just a reduction in food waste at the household level but a more sustainable and conscious global community.

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