Exploring the Role of AI in Enhancing Sustainability within New Zealand's Hospitality Industry: A Study on Knowledge, Applicability, and Perception in Reducing Food Waste

Melanie Thushara Perera

A thesis submitted in partial fulfilment of the degree
Master of Applied Management
at Otago Polytechnic Auckland International Campus,
Auckland,
New Zealand

May 2024

Declaration Concerning Thesis Presented for the Degree of Master of Applied Management

I, Melanie Thushara Perera

of

solemnly and sincerely declare, in relation to the thesis entitled:

Exploring the Role of AI in Enhancing Sustainability within New Zealand's Hospitality Industry: A Study on Knowledge, Applicability, and Perception in Reducing Food Waste

That work was done by me

and

a) The material has not previously been accepted in whole, or in part, for any other degree or diploma

Signature: …………………………………………………………

Date: 08/05/2024

Abstract

The hospitality industry in New Zealand is a noteworthy contributor towards the country's Gross Domestic Product, however, it is also responsible for a significant amount of food waste (FW). In recent years, there has been a growing interest globally in artificial intelligence (AI) to curb FW in the hospitality industry. This study explores the role of AI in reducing FW and enhancing sustainability within New Zealand's hospitality industry, specifically, it focuses on the factors critical for its implementation - knowledge, attitudes, and perceptions of hospitality stakeholders. The study adopted a mixed-methods approach involving quantitative and qualitative data collection from 131 industry professionals.

The data suggests that the sample is skewed towards the lower end of FW, requiring caution due to inconsistent self-reported data with audits (Chisnall, 2017). A quarter were unsure or found it difficult to estimate avoidable food waste (AFW), potentially indicating a lack of awareness or difficulty measuring FW accurately. Inaccurate demand forecasting is the primary cause of FW in catering services and cafes/coffee shops, while portion control and plate waste are cited as the main causes of FW in fine-dining restaurants and pubs. A lack of FW awareness is the leading cause of FW in hotels/resorts and fast-food outlets. The diverse range of challenges faced by the hospitality industry provides insights into the areas where improvements can be made to increase efficiency, reduce waste, and enhance customer satisfaction.

The study found a general lack of awareness and knowledge about AI among hospitality professionals, yet an openness to adopting AI-driven technologies for FW reduction. Challenges such as cost-effectiveness and proven effectiveness are key causes hindering AI adoption. Increased awareness and promotion of AI's return on investment could decrease scepticism and facilitate effective integration into FW reduction strategies. Finally, this research underlines the need for collaborative efforts among industry professionals, policymakers, and technology developers to overcome existing hurdles and leverage AI for sustainable practices in the hospitality sector in New Zealand.

Acknowledgement

This thesis is the culmination of interwoven journeys, both academic and personal. My deepest gratitude goes to my late parents. Though they cannot be here to celebrate this milestone, their unwavering belief in the power of education and the dedicated support they instilled in me fuelled the fire of curiosity that led me on this path. This thesis is a tribute to their legacy.

I am immensely grateful to my supervisors, Dr. Shafiq Alam and Dr. Indrapriya Kularatne. Dr. Alam's depth of knowledge and challenging questions sharpened my thinking, while Dr. Kularatne's proficiency and meticulous attention to detail ensured rigour. Your combined expertise provided a perfect balance, and I am incredibly fortunate to have learned from both of you. Special thanks to the Otago Polytechnic Auckland International Campus for providing the necessary tools and support to pursue this research.

To my husband Suwan and sons, Manith and Dishen, words cannot express my appreciation for your encouragement and understanding throughout this journey. Your patience as I juggled research and family life holds a special place in my heart.

My sister, Anushi, your keen eye for detail helped me locate countless articles, and your dedicated support was a constant source of strength. My sister, Shamila, and my brother-in-law, Hareen, your efforts in coordinating responses during my research were invaluable. You went above and beyond to reach out to your network, helping me access a wider population for my research. Your willingness to lend a hand exemplifies the true spirit of collaboration. I am truly grateful to all my friends who provided support in various ways. Finally, and most importantly, a special thank you to the participants who shared their insights. You are the backbone of this research. Your diverse perspectives and experiences have broadened my understanding of the research topic and added depth to my analysis.

This thesis journey has been a learning experience filled with challenges and triumphs. On this momentous occasion, I look back with profound gratitude for the incredible support network. Thank you to all of you. This achievement would not have been possible without each one of you. As I step forward, I do so with a heart brimming with gratitude!

Table of Contents

List of Tables

List of Figures

Abbreviations

FW /AFW	-	Food Waste/Avoidable Food Waste
FL/FLW	-	Food Loss/ Food Loss and Waste
AI	-	Artificial Intelligence
SDG	-	Sustainable Development Goals
BCG	-	Boston Consultancy Group
FSC	-	Food Supply Chain
ML	-	Machine Learning
DL	-	Deep Learning
IoT	-	Internet of Things
E-Nose	-	Electronic Nose
E-Tongue	-	Electronic Tongue
KNN	-	k-nearest neighbour
CNN	-	Convolutional Neural Network
CV	-	Computer Vision
RF	-	Random Forest
ANN	-	Artificial Neural Network
UNDP	-	United Nations Development Programme
OECD	-	Organisation for Economic Co-operation and Development
GDP	-	Gross Domestic Product
WHO	-	World Health Organisation
VOC	-	Volatile Organic Compounds
KPIs	-	Key Performance Indicators
MVC	-	Model-View-Controller
SMEs	-	Small and Medium Sized Enterprises
MBIE	-	Ministry of Business Innovation & Employment

Chapter 1 - Introduction

Background

The hospitality industry, worth USD 4.7 trillion in 2023 (Statista, 2023), significantly contributes to the global economy, nearly 10% of the Gross Domestic Product (GDP). It provides one in every ten jobs, according to the OECD's 2018 report. The New Zealand hospitality sector significantly contributes to the economy adding 6.6% to the GDP (Infometrics, 2021). It employed over 64,000 people across almost 31,000 businesses in 2021 (Ministry of Business, Innovation & Employment, 2024) (MBIE) and contributed over NZD 14 billion in industry sales in 2022 (Restaurant Association of New Zealand, 2023).

The main sectors within the hospitality industry, as detailed by the Australia New Zealand Standard Industrial Classification, are accommodation, cafes and restaurants, takeaway food services, catering services, pubs, taverns and bars and hospitality clubs (MBIE, 2024).

Despite contributing significantly to the economy, the hospitality industry also contributes to food waste (FW). Commercial food service, which includes the hospitality sector, ranks third in the food value chain in terms of the quantity of FW produced (Martin-Rios et al., 2020). Research within New Zealand's hospitality sector, notably by Chisnall (2017) and WasteMINZ in 2018 found that restaurants and cafes alone generate 24,375 tonnes of FW annually, with 61% being avoidable.

Food loss (FL) and FW have been referred to interchangeably by certain academics (Betz et al., 2015), however, other researchers have made a distinction between the two (Gustafsson et al., 2011). Hence, there is debate over the precise definition of FL and FW (Chauhan et al., 2021). The Ministry for Environment (2022) defines FL as food that leaves the supply chain before harvest or slaughter, while FW includes food that leaves the supply chain from wholesale, retail, and marketing stages, including consumption. Understanding this distinction is key, as tackling FW requires targeted interventions at various points within the food system (Ministry for Environment, 2022).

A study by Dhir et al. (2020) highlights the significant impact of FW on sustainability. The World Commission on Environment and Development defines sustainability as meeting the present generation's needs without compromising future generations' ability to meet their needs; encompassing environment, economy, and equity (United Nations, 2024). The hospitality sector being a major player in the economy must address the issue of FW and the resultant sustainability challenges to align its operations with the Sustainable Development Goals [1](SDGs) (Voukkali et al., 2023). If this magnitude of waste is to be substantially reduced, a significant change in how food is produced and consumed in the hospitality sector is necessary (Pirani & Arafat, 2016). While Lee and Huang (2023) are of the view that despite technological advancements, there is a concerning increase in FW, Teerlink (2019), stresses that FW can be significantly decreased by using technologies such as artificial intelligence (AI) and machine learning (ML).

This study explores the understanding and perspectives regarding using AI to reduce FW within New Zealand's hospitality sector. Additionally, the research will explore the role of AI in advancing the sustainability goals of the hospitality sector.

The Rationale of the Study

This study's rationale addresses the importance of using AI to reduce FW in New Zealand's hospitality industry. The successful implementation of AI in this industry requires an in-depth understanding of its stakeholders' knowledge, perceptions, and attitudes. Stakeholders in this context include individuals or organisations with a vested interest in the business's decision-making and activities, including owners/shareholders, managers, chefs, kitchen staff, and wait staff.

The coronavirus pandemic has shown the need for companies to become more flexible and resilient to unforeseen events. Furthermore, it has emphasised the importance of reducing FW and enhancing sustainability efforts in the hospitality industry due to the economic and environmental impacts caused by the pandemic. Thus, it is imperative to

[1] The United Nations adopted the Sustainable Development Goals in 2015 to eradicate poverty, safeguard the environment, and guarantee peace and prosperity for all by 2030 (UNDP, 2023).

identify innovative solutions using AI-powered approaches that can address FW holistically and contribute to overall sustainability efforts.

The study's findings will provide insights into stakeholders' attitudes towards AI adoption in the hospitality industry and contribute to the knowledge of AI on FW reduction. The study's recommendations will guide hospitality businesses in New Zealand to adopt effective strategies to reduce FW and contribute proactively to overall sustainability efforts.

The Problem Statement

Food waste within the New Zealand hospitality industry poses a significant environmental, economic, and social challenge. Artificial intelligence can create positive impacts on humans and accelerate sustainable outcomes. However, this potential can be fully realised only if stakeholders have confidence in AI as an exponential technology for good, according to Hinish (2023). While almost two-thirds of chief executives globally see AI as a force for good, more work still needs to be done to address risks and possible unintended concerns, as per CEO Outlook Pulse (2024). Hence, while solutions such as AI show promise, limited knowledge and diverse stakeholder perceptions create a barrier to its effective implementation, which is true for the hospitality industry. This lack of understanding hinders the industry's ability to identify key factors contributing to FW, acknowledge the potential benefits of AI in waste reduction and develop strategies to overcome potential challenges associated with AI adoption. By addressing these challenges, the research will pave the way for the strategic use of AI and ultimately contribute to a more sustainable future for New Zealand's hospitality industry.

Research Aims and Objectives

The study aims to;

I. Explore the role of AI in enhancing sustainability within New Zealand's hospitality industry.

II. Understand the knowledge and awareness of AI among hospitality industry professionals in New Zealand.

III. Investigate the applicability of AI in reducing FW in the hospitality industry in New Zealand.
IV. Examine hospitality industry professionals' perceptions towards using AI in reducing FW.
V. Identify the challenges and opportunities associated with implementing AI in reducing FW in the hospitality industry in New Zealand.

In terms of the research boundaries, the study investigates the role of AI in enhancing sustainability in New Zealand's hospitality industry, focusing on knowledge, applicability, and perception in reducing FW. It does not explore FL, quantify FW, or provide recommendations for AI implementation. The study utilises the Ministry for Environment's 2022 definition of FW and Australia New Zealand Standard Industrial Classification to define the hospitality industry.

Research Questions

Based on the above objectives the following questions were framed for this study.

I. How can AI effectively reduce FW within the hospitality industry?
II. What are hospitality industry stakeholders' knowledge, perceptions and attitudes towards integrating AI for FW reduction, and how do these perceptions influence AI adoption and its efficacy?
III. How does the employment of AI in FW reduction align with and enhance the overall sustainability efforts of companies operating in the hospitality sector?

Research question one is primarily discussed and analysed in Chapter 2, where a review of literature contributions by scholars on various applications of AI and its successful implementation, along with case studies, is presented. Furthermore, research question one is also discussed in Chapter 5. On the other hand, research questions two and three are analysed from the survey results and are primarily discussed in Chapters 4 and 5.

To investigate the above research questions, this study employed a mixed-methods approach. It used an online survey, open-ended questions, and secondary data analysis to gather quantitative and qualitative insights.

Significance of the Study

The significance of this study lies in its potential to address the urgent issue of FW in New Zealand's hospitality sector. The hospitality industry is a significant contributor to FW, which not only has economic consequences but also environmental and social implications. Therefore, the successful implementation of AI-driven solutions can lead to significant benefits, such as reducing resource consumption, lowering greenhouse gas emissions, and promoting a more sustainable future for the sector and the country.

This study also highlights the importance of understanding stakeholders' attitudes, perceptions, and knowledge towards AI and its potential for FW reduction. The findings can inform targeted policies and incentives to support AI adoption within the hospitality sector. Furthermore, the study's identification of key barriers can guide stakeholders towards successful AI implementation to reduce FW.

The research can also contribute to the broader literature on AI and FW reduction by examining the potential of AI within New Zealand's unique hospitality landscape. Furthermore, the results can identify knowledge gaps and pave the way for further research on specific AI technologies and their effectiveness in diverse hospitality contexts. Hence, the study underscores the potential of AI-driven solutions to significantly reduce FW in New Zealand's hospitality sector, highlighting the importance of stakeholder engagement and paving the way for further research and targeted policies to support AI adoption.

Structure of the Thesis

Chapter 2 of the study explores FW in the hospitality industry, focusing on its scope, causes, and economic, social and environmental impacts. It discusses current practices and initiatives to reduce FW, the effectiveness of AI technologies, and case studies of successful AI implementations. The methodology is detailed in Chapter 3, including research design, data collection methods, ethical considerations, and data privacy protection. Chapter 4 presents data and findings, while Chapter 5 discusses the findings, identifying implications for understanding the role of FW and AI in the hospitality industry. Chapter 6 offers actionable strategies, study limitations, and further research and exploration in this field.

Chapter 2- Background and Literature Review

This chapter examines the literature on FW in the hospitality industry, with a global focus and specific attention to New Zealand. It discusses different FW categories, their economic and environmental impacts, and current practices to reduce them. Furthermore, the chapter discusses the potential of AI technologies for optimising food production, purchasing, and inventory management. Likewise, it analyses successful AI implementations in hospitality settings, examining the benefits and challenges of AI adoption and identifying gaps in existing knowledge.

Food Loss and Food Waste: A Varied Landscape

The terms FL and FW are used interchangeably or commonly by scholars as food loss and waste (FLW), contributing to different perspectives on their classification (Chauhan et al., 2021). Distinguishing between FL and FW is crucial for targeted interventions, resource allocation, monitoring progress, and advocacy (Ministry for Environment, 2022). Chauhan et al. (2021) categorised FLW definitions into five major groups: Food supply chain (FSC) stage; human edibility; quality of food; nature of use; and destination of food. Food loss and FW are often considered subsets of each other (Buzby et al., 2014) in the first category of FSC. Some scholars acknowledge the distinction between FL and FW, suggesting losses from the farm through to processing are labelled FL, while FW occurs later in the process and is often due to consumer behaviour (Gustavsson et al., 2011).

The second category of FW focuses on edible food and its intention of production. Food intended for human consumption is FW (Beretta et al., 2013), while wastage along FSCs regardless of intent is FW (Griffin et al., 2008). Discarded edible food is referred to as 'avoidable' or 'unavoidable waste' if it is never suitable for human consumption (Secondi et al., 2015) and ‘potentially avoidable’ applies to certain types of waste that are sometimes consumed but not always (Papargyropoulou et al., 2014). The third category is based on quality (Porter et al., 2018), while the fourth is based on nature, with unplanned use being FLW (Parfitt et al., 2010) while Bellemare et al. (2017) are of the view that productive food (e.g. manure) should not be wasted. The destination of surplus food significantly influences its classification as waste. Rethink Food Waste (2016) defines FW as all food used as landfill scrap, including on-farm losses. Hence, there is debate over the precise definition of FLW (Chauhan et al., 2021).

The Ministry for Environment (2022) defines FL and FW used in New Zealand. According to their explanation, the distinction between FL and FW depends on when the food product exits the supply chain. Pre-harvest food, or food that leaves the FSC before it is ready for harvesting, is not included in the definition. Food loss refers to food that leaves the supply chain when the food is ready for harvest (or slaughter) and proceeds to the processing and manufacturing stage. Food waste on the other hand is food that leaves the supply chain from the wholesale, retail and marketing stages onwards. This includes waste at the consumption stage (at home or away from home).

Food Waste and Sustainability: A Multi-Dimensional Issue

Food loss and waste are global issues, with 1.3 billion tons of food produced annually, worth USD 1 trillion being wasted (World Food Programme, 2020). The Boston Consulting Group (BCG) predicts that by 2030, FW will reach 2.1 billion tons, worth USD 1.5 trillion, equivalent to 66 tons of food wasted per second. This highlights the urgent need for sustainable food production (BCG, 2022).

Food waste has serious implications for sustainability and the environment, as highlighted by Dhir et al. (2020). This issue has been identified as a major unsustainability hot spot by Eriksson et al. (2018). The main concerns related to FW include its contribution to climate change (Kallbekken & Sælen, 2013), the financial losses associated with it (Hennchen, 2019), its impact on food security (Wang et al., 2021), and its overall economic impact (Heikkilä et al., 2016). These concerns are supported by estimates suggesting that FW results in an economic loss of 23% of all food purchased (Papargyropoulou et al., 2019).

Food loss and FW result in the emission of around 4.4 gigatonnes of greenhouse gases. If FW were a country, it would be the third-largest carbon dioxide emitter in the world, after China and the USA (World Food Programme, 2020). Furthermore, FW uses up to 21%

of freshwater, 19% of fertilisers, 18% of cropland, and 21% of landfill volume, which are finite resources (Lewis, 2022).

Despite sufficient food production globally, 828 million people, or approximately 10% of the world's population, suffer from hunger (WHO, 2022). If 25% of the food lost or wasted worldwide were saved, it would feed 870 million people (Teerlink, 2019). Moreover, hunger kills more people than AIDS, malaria, and tuberculosis combined. Besides, it is a significant ethical concern (Kuleshov et al., 2019; Martin-Rios et al., 2019).

The situation in New Zealand is comparable to global issues. Food and Organic waste account for 9% of New Zealand's biogenic methane emissions and 4% of total greenhouse gas emissions (Ministry for Environment, 2022). The Kantar New Zealand Food Waste Survey 2023 by Rabobank and Kiwi Harvest reveals that annually, over 100,000 tonnes of edible food are wasted in New Zealand (Kantar, 2023). The estimated value of FW per household is $1510 annually, resulting in $3.2 billion of wasted food nationally. This translates to millions of dollars in lost revenue, avoidable environmental impact and the capacity to feed 336,000 people annually (Ministry for the Environment, 2022). Moreover, while one in five children in New Zealand experience food insecurity (Ministry for Environment, 2022), the irony of edible food ending up in landfills underscores the social injustice inherent in the system. The issue of FW in New Zealand is undoubtedly complex.

Critical Role of Food Waste in the Hospitality Industry

The hospitality industry is vast and segmented and there appear major overlaps. Hemmington (2007) questions whether the hospitality industry is a service industry, whether it is entertainment, art, theatre, or retailing, or whether it is no more than another form of business. Hemmington (2007) opinioned that the industry's growth is hindered by a lack of clear definition and understanding of hospitality as a commercial phenomenon. The hospitality sector includes commercial and social aspects and is divided into profit and cost sectors (Marthinsen et al., 2012). The profit sector includes hotels, restaurants, and catering, while the cost sector includes accommodation and food service in establishments such as schools, universities, and healthcare (Marthinsen et al., 2012). According to Dhir et al.

(2020), the hospitality and food service sector can be divided into three key segments: business, education, and healthcare.

According to Williams et al. (2011), the hospitality industry is responsible for a significant amount of waste, more than one-third of which is FW. The Natural Resources Defense Council estimates that between 4% to 10% of food purchased by restaurants becomes kitchen loss before reaching the consumer (Gunders, 2019). Research by Chisnall (2017) and WasteMINZ (2018) in New Zealand's hospitality sector revealed that restaurants and cafes generate 24,375 tonnes of FW annually, with 61% being avoidable and over 50% of avoidable waste remaining preventable. The significant aspects of the issues mentioned above are discussed in detail in the following sections.

Causes of Food Waste in the Hospitality Industry: Multitude of Factors

Understanding the various factors contributing to FW is crucial for developing effective reduction strategies. This section explores numerous causes of FW identified by researchers and measures proposed to combat it. In addition, it explores the findings of research carried out in New Zealand's hospitality sector.

Based on Chisnall (2017) and WasteMINZ research in 2018, FW is divided into three categories: spoilage, preparation waste, and plate waste.

Preparation Waste

Preparation waste is the largest fraction of total FW (Papargyropoulou et al., 2019; WasteMINZ, 2018). Of the total FW in the cafes and restaurants in New Zealand, preparation waste was as high as 60% (WasteMINZ, 2018). Food waste generated in the kitchen includes items such as vegetable peelings, eggshells, burnt toast and any unsold food items at the end of the day (WasteMINZ, 2018).

The nature of the food menu, production processes, and the use of pre-prepared versus whole-food products are key factors contributing to preparation waste (McAdams et al., 2019). Additionally, the skill levels of employees, product development, procurement practices, portion sizes, cultural influences, inventory management, and environmental sensitivity are other factors that contribute to preparation waste (Kasavan et al., 2019).

Spoilage

WasteMINZ's 2018 report shows that spoilage accounted for 7% of all FW. This happens when ingredients are over-purchased or not rotated properly, resulting in the spoiling of food even before it can be used.

Factors such as the type of food served and the use of convenience or pre-prepared foods can affect spoilage (Amit et al., 2017). Rigid product specifications for fresh produce may result in the wastage of still-edible but below-standard products instead of using them as intended (Derqui et al., 2016). According to Bhajan et al. (2022), factors such as prolonged storage of raw materials, physical damage, browning, staling, and fungal growth are significant contributors to FW.

Plate Waste

One-third of total FW is due to plate waste, which is food left uneaten on customers' plates (WasteMINZ, 2018). The size of dinnerware significantly contributes to plate waste, as noted by Wansink and van Ittersum (2013). Other factors that contribute to plate waste include behavioural and socio-cultural habits, portion sizes, preferences, storage practices, and the type of food served (Goldenberg, 2018).

The other reasons for FW include different service styles, such as à la carte, open buffet, and catering events, which have different effects on FW (Bhajan et al., 2022; Uğur Genç et al., 2019). Uğur Genç et al. (2019) suggest that à la carte service produces less waste than events or buffets, but individual orders are mentioned as a reason for reducing waste. Customers often order from the menu without knowing the portion of the food to be served, leading to waste. High-end hotel customers' prioritisation of appearance, hygiene, taste, and quality of ingredients can lead to FW. Moreover, chefs' classification of ingredients as edible and inedible, and their focus on serving only the best-looking produce, can displace organic waste and contribute to overall waste management in high-end hotels (Bhajan et al.; 2022; Papargyropoulou et al., 2019). Uğur Genç et al. (2019) claim that because of the classification of edible vs inedible, chefs are of the view that the resultant waste is necessary.

Looking at FW in different settings, casual dining shows more plate waste, while fine dining has higher waste per customer. High-end establishments produce the most overall waste (Aamir et al., 2018; McAdams et al., 2019). Larger restaurants have lower per-employee waste, while events such as banquets generate more waste than private meals (Tatàno et al., 2017). Restaurants have a four-fold higher waste per portion compared to canteens, highlighting the importance of portion control in reducing waste (Malefors et al., 2019). According to a recent study by Tomaszewska et al. (2021), the amount of plate waste generated is strongly associated with the type and form of catering service. The study found that the largest proportion of plate waste was generated during breakfasts served as a self-service buffet, while the smallest amount of plate waste was recorded in restaurants where dishes were served à la carte.

Concisely, the hospitality industry is a major contributor to FW, with preparation waste being the largest fraction. Understanding the causes of FW is critical in developing effective reduction strategies to combat this problem.

Guide to Reducing Food Waste in the Hospitality Industry

To combat the issue of FW, various measures have been proposed in the literature, including employee training on proper food handling, hygiene, and serving practices, as well as multilateral consumer education on the negative impact of FW and individual actions to reduce it (Tomaszewska et al., 2021). Kasavan et al. (2019) suggest that effective inventory management practices, portion control measures, and employee training programs can help reduce preparation waste in the hospitality sector. Derqui et al. (2016) argue that relaxing product specifications and implementing effective quality control measures can help reduce spoilage in the hospitality sector. Amit et al. (2017) suggest that using fresh, whole foods and implementing effective inventory management practices can help reduce spoilage. Goldenberg (2018) suggests that reducing portion sizes, offering flexible menus, and educating customers on the environmental impacts of FW help lessen plate waste. Other proposed measures include; menu planning with smaller portions, utilising leftovers creatively, and featuring local, seasonal ingredients (McAdams et al., 2019), implementing efficient inventory management systems to minimise overstocking and expiration (Kasavan et al., 2019), investing in proper storage facilities and equipment to prevent spoilage (Amit et al., 2017), utilising technology to optimise temperature control and track inventory (Papargyropoulou et al., 2019), and collaborating with food banks and composting facilities to divert FW from landfills (Mainvil et al., 2018). In addition, design strategies such as the intelligent menu design, the 'root-to-stem' concept, and the 'adaptive buffet' approach have been proposed to reduce FW by changing consumer behaviour and perception (Uğur Genç et al., 2019).

Briefly, the hospitality industry produces significant FW, ranging from scraps to leftovers. According to Chisnall (2017), it is important to identify the root causes of pre-consumer and post-consumer waste to implement sustainable strategies. Pre-consumer waste refers to the food discarded during food preparation, while post-consumer waste refers to the food left unconsumed by customers.

To reduce the amount of FW, the hospitality industry could consider implementing strategies ranging from menu planning that prioritises using ingredients that are about to spoil to food donation programs and composting. By taking these steps, the hospitality industry can reduce its environmental impact and improve its bottom line as it saves money on food costs.

Food Waste in the Hospitality Industry in New Zealand

Food waste represents a significant challenge for New Zealand's hospitality sector, with research by Chisnall (2017), Jones (2017), and WasteMINZ (2018) providing valuable insights into the scope of the problem and potential solutions.

These studies consistently highlight the alarming scale of FW, with WasteMINZ (2018) estimating that restaurants and cafes discard 24,375 tonnes annually. Even more concerning is that a substantial portion, 61%, according to Chisnall (2017) and WasteMINZ (2018), is classified as avoidable food waste (AFW). Avoidable food waste presents a clear opportunity for significant reduction through improved practices as the difference in AFW between the best and the worst-performing cafes and restaurants was 43%. Chisnall's 2017 study only analysed FW and excluded drink waste. It is important to note that coffee grounds are a significant source of waste for cafes and some restaurants (Chisnall, 2017).

Breaking down the types of FW, Chisnall (2017) identified preparation waste (60%) and plate waste (33%) as the primary causes of FW. Vegetables were the most commonly discarded food item (28%), followed by bakery products (26%), meat (13%), and fruit (9%) (Chisnall, 2017). Interestingly, Chisnall (2017) found no correlation between business size and AFW, suggesting that staff awareness and skillset may be more critical factors. However, there is a correlation between FW and the number of customers served, as well as the size of the business with FW.

Jones' (2017) research reinforces these findings. Their investigation of 10 restaurants and cafes revealed a similar waste composition, with preparation waste (55.4%) as the leading cause of FW, followed by plate waste (27.2%) and spoilage (17.4%). Vegetables (39%) were again the most wasted food group, followed by dairy (18%), meat (16%), and bakery items (11%) (Jones, 2017). Notably, Jones (2017) concurred with the high proportion of AFW, estimating that 75% could be eliminated or reduced.

A concerning trend emerged regarding businesses' self-awareness of FW. Jones (2017) and Chisnall (2017) documented a significant discrepancy between self-reported and quantified FW through audits. Businesses significantly underestimated AFW, with self-reported figures ranging from less than 20% to over 50% lower than those obtained through audits (Jones, 2017; Chisnall, 2017). This underestimation suggests potential limitations in business practices or awareness regarding FW measurement. Jones (2017) suggests a lack of clarity around the definition of AFW might be leading to underestimates, while Chisnall (2017) highlights the possibility of businesses being unwilling to acknowledge the accurate scale of the issue or lacking appropriate monitoring practices.

Compounding the problem is a concerning level of complacency among businesses regarding their current waste levels. Many businesses in Jones' (2017) study expressed satisfaction with their waste reduction practices despite significant AFW identified through audits. Similarly, Chisnall (2017) found comfort with current waste generation, potentially hindering motivation for further reduction efforts. This complacency might be linked to the perception of customer behaviour as the primary contributor to FW, as Chisnall (2017) suggested.

Overall, the researches by Chisnall (2017), Jones (2017), and WasteMINZ (2018) paint a clear picture of a hospitality sector struggling with significant FW generation. However, these studies also highlight a substantial opportunity for reduction through improved FW measurement, staff training, and the implementation of various strategies. These strategies include offering smaller portions and optional sides, better stock rotation to minimise spoilage, utilising vegetable scraps for broths or sauces, donating surplus food to charities, and, most importantly, fostering a culture of awareness and accountability around FW reduction within businesses. Moreover, the government should support a voluntary commitment to encourage organisations to measure FW, leading to the development of universal toolkits and consultancy services for waste prevention and management (New Zealand Food Waste Champions 12.3 Trust, n.d.).

AI-Powered Strategies for Effectively Reducing Food Waste Throughout the Supply Chain

Food waste occurs at all stages of the supply chain, from the farm to the consumer and, according to UNEP (2021), it is estimated at 40% of global food production. The retail and consumer stages significantly contribute to FW in developed countries. In developing countries, however, the most significant waste occurs at the farm due to limited technology adoption (Kuleshov et al., 2019).

The hospitality industry stands to revolutionise its approach to FW and sustainability by leveraging AI and tech applications from diverse sectors in the supply chain (Onyeaka et al., 2023; Singh et al., 2024). Artificial intelligence is a machine's ability to perform the cognitive functions we usually associate with human minds (McKinsey & Company, 2023). AI-powered applications are explained in Appendix 1. Integrating AI and the Internet of Things (IoT) has given rise to the 'Internet of Food', offering a comprehensive solution to address FW across the entire supply chain (Sharma et al., 2022). The following section investigates the diverse applications of AI, exploring its impact on the supply chain. Appendix 2 provides a summary of the applications utilised in FSC.

Artificial Intelligence Optimises Farm Management

Artificial intelligence has become a crucial tool in modern agriculture, aiding farmers in crop selection, hybrid seed selection, and resource management through weather, soil, and irrigation monitoring (Sharma et al., 2022). It also helps make informed decisions to reduce FW and increase crop yield (I. Kumar et al., 2021). Integrating sensors and ML algorithms with traditional farming methods can lead to more precise decision-making, such as identifying fruit maturity and microorganisms that enhance fruit and vegetable growth (T. Kumar et al., 2022). AI-based disease detection models and IoT-based systems can accurately predict crop diseases, increasing yield and reducing FW (Chung et al., 2022). A mobile application-based solution uses ML, deep learning (DL), and image processing concepts for crop prediction, price prediction, pest detection, and cloud marketing (Hennayaka et al., 2022).

Production and Processing with Artificial Intelligence

The use of AI technologies in food production and processing is increasing rapidly, as it offers numerous benefits such as improving efficiency, reducing waste, and increasing food safety (Konfo et al., 2023). Garre et al., (2020) highlighted that ML models can identify production anomalies and FW. Similarly, non-destructive identification methods for potatoes unsuitable for French fry production have been developed using broadband reflection spectroscopy and ML algorithms (Smeesters et al., 2021). In addition, an IoT-based waste tracking system is proposed to identify and measure damaged potatoes, identify waste generation causes, and utilise image processing and load cell technologies. (Jagtap et al., 2019).

Intelligent Storage Systems with Artificial Intelligence

Intelligent storage systems powered by AI empower informed decision-making regarding food quality and shelf life. Henrichs and Krupitzer (2022) presented an adaptive software system using smart sensors to monitor packaged food conditions, employing ML for quality and shelf life predictions. Pounds et al. (2022) highlighted the importance of real-time food quality detection for consumers. Their sensor film and k-nearest neighbour (KNN) algorithm rapidly monitor food freshness, potentially leading to reduced waste. N. Kumar et al. (2020) proposed an autonomous warehouse system using ML and Blockchain technology to address FW in traditional warehouses, which are crucial for storing non-seasonal food products in supermarkets. Optimising storage conditions based on real-time data, these advancements ensure product longevity and minimise spoilage (Pounds et al., 2022).

Supermarket Streamlining with Artificial Intelligence

AI-powered technologies have been gaining traction in the retail industry as a solution to reduce FW in supermarkets. Kuleshov et al. (2019) developed a reinforcement learning engine to automate supply chain decisions, reducing FW by 50% in real-time with a US grocery chain. Shanthini et al. (2021) developed an AI-based expiry date extraction method for packaged food, which involved object detection and text recognition to improve consumer awareness of food freshness and potentially reduce FW. Wijaya and Nugraha (2021) proposed an IoT device that can detect meat's expiration time using a gas sensor. Karamchandani et al. (2021) suggested a method to determine the shelf life of fruits using e-nose and ML. Soltani et al. (2021) developed three model-free classification algorithms for supermarket refrigeration systems to improve efficiency and reduce FW caused by poor decision-making.

Empowering Households with Artificial Intelligence

Artificial intelligence is increasingly being used to reduce FW in households. Rezgui et al. (2020) proposed an AI system that uses convolutional neural networks (CNNs) to prevent FW in Canadian households. The system analysed pictures of fruits taken using cell phones to determine their maturity state and recommended when to consume or discard them. Woolley et al. (2020) developed a product service system that allows consumers to plan and purchase items based on available food and consumer preferences. The system uses AI to match recipes with available ingredients, reducing FW at both consumer and supply chain levels. Additionally, the E-COmate system, an augmented bin that measures

FW and provides direct feedback to users via a tablet, aims to redirect behaviour and promote food sustainability through transparency and social influence strategies (Lim et al., 2015). After installing E-COmate in their kitchens, participants showed a significant overall decrease in FW, particularly a 32% decrease in edible or once-edible FW (Lim et al., 2015). These AI-powered solutions offer practical solutions to minimise FW in households.

Briefly, the literature explores various AI-powered applications that aim to reduce FW at various stages of the supply chain.

Artificial Intelligence and its Various Applications in Tackling Food Waste in the Hospitality Industry

The hospitality sector has traditionally relied on personalised services and human interaction to create memorable experiences for guests. However, advancements in AI have prompted the industry to embrace innovative technologies, revolutionising conventional hospitality practices (Ruel & Njoku, 2021). The introduction of AI, automation, and robotics technologies under Industry 4.0 has enabled businesses to strategically address daily management challenges (Li, Bonn & Ye, 2019). These technologies are increasingly being integrated into hospitality settings worldwide, with service automation systems incorporating AI and robots to streamline processes and expedite tasks traditionally carried out by front-line service staff (Makridakis, 2017). Robotics and automation technologies are now being utilised for activities such as food preparation, cooking, and serving, offering opportunities to optimise operations, reduce costs, and enhance food safety and quality (Goyal & Singh, 2021). This evolution is expected to drive significant changes within the hospitality industry.

Studies across diverse contexts, from India's street food vendors (Gondaliya & Sharma, 2023) to university cafeterias (Dhir et al., 2020), and restaurants and hotels (Damaren, 2023) highlight the multifaceted benefits of AI in reducing FW. One key advantage lies in improved demand forecasting. AI algorithms can analyse vast datasets, incorporating historical sales, customer preferences, and weather patterns (Dombroski, 2023). This leads to more accurate predictions, enabling smarter inventory management and production planning, ultimately minimising overproduction and excess food (Gondaliya &

Sharma, 2023). This does not only reduce waste and optimise costs but also increases profits. For instance, using AI for FW reduction saw a 30% increase in profits in restaurants in China (Lamba, 2021).

Artificial intelligence empowers businesses to gain deeper insights into FW patterns. Smart devices track discarded food, providing valuable data on types, quantities, and costs (Martin-Rios et al., 2018). This information empowers informed decision-making, allowing chefs to adjust menus, optimise portion sizes, and identify areas for improvement (Ben Youssef & Zeqiri, 2022). Additionally, AI-powered sensors can monitor raw materials in real-time, alerting businesses to potential spoilage and enabling timely interventions (Gondaliya & Sharma, 2023).

Beyond cost savings, AI holds the potential to enhance customer satisfaction. AI-powered systems can personalise menus based on individual preferences, increasing satisfaction and reducing plate waste (Gondaliya & Sharma, 2023). Additionally, AI-driven apps such as Too Good To Go connect restaurants with consumers willing to purchase unsold food at discounted prices, promoting responsible consumption and further minimising waste. The Macau case study by Cheng and Leong (2023) demonstrates the power of AI to analyse, educate, and optimise every stage of the food journey, paving the way for a future where delicious meals coexist with sustainable practices.

Concisely, the integration of AI offers a plethora of advantages for reducing FW within the hospitality sector. From improved forecasting and data-driven insights to proactive management and personalised experiences, AI paves the way for a more sustainable and responsible future for the industry.

The following section explores the literature on various AI applications discussed in the context of the hospitality industry. This section is organised to mirror the AI applications for FW management cited in Onyeaka et al.'s 2023 research. These are; smart monitoring and analytics, AI-powered predictive analytics, AI-powered inventory management, AI for consumer awareness and education and AI-based donations and redistribution. Appendix 3 provides a summary of the applications utilised in the hospitality sector.

Smart Monitoring and Analytics

AI-enabled sensors and data analytics make it possible to monitor food quality, storage conditions, and expiration dates in real-time. This allows for proactive measures to prevent waste (Onyeaka et al., 2023).

AI-Powered Dish Waste Detection

Restaurants can significantly reduce waste by monitoring and eliminating dishes that generate excessive waste. Pu et al. (2022) developed a method to detect dish waste in restaurants using image processing and DL technology. By collecting images before and after consumption, the accuracy of label recognition was improved by 98.47% compared to traditional single-image data. This innovative approach demonstrated the effectiveness of image processing and DL in waste detection and its potential to revolutionise food industry waste reduction practices (Pu et al., 2022).

AI-Powered Food Intake Estimation

Wasted food not only denies the provision of essential nutrients to those in need but also negatively impacts their overall well-being. Accurate food intake estimation is essential for public health organisations, customers, and restaurants. Customers can track the nutritional values of their food portions, while restaurants can minimise waste and develop data-driven production control. Accurate data collection methods help understand individual behaviour and choices regarding nutritional intake and FW. A novel tool developed by Sarapisto et al. (2022) used ceiling-mounted cameras and computer vision (CV) to estimate food intake accurately in controlled environments. The study demonstrated high accuracy in meal type identification, allowing for automated food intake monitoring. By providing accurate data for public health organisations, customers, and restaurants, these systems can help minimise FW, improve nutritional intake, and promote overall well-being (Sarapisto et al., 2022).

Smart Dining Halls

The issue of FW in college dining is a significant concern in the USA, with an average student wasting around 140 pounds of food annually (Poon, 2019). To combat this, innovative models such as CNN-based image processing, CompostNet, and U-Net deep convolutional networks are being developed. A study by Farinella et al. (2020) investigated the combination of these methods to decrease FW in a university dining hall. The dining hall relied on past food usage data to influence current inventories and menus. The team used ML to train a CNN to identify common food items in the dining hall, using a Raspberry Pi with connected sensors and a remote database server showcasing the potential to significantly reduce FW in college dining.

Smart Waste Management

Hong et al. (2014) and Wen et al. (2018) have proposed IoT-based waste management systems. Wen et al. (2018) developed an IoT-based waste management system for restaurants in Suzhou, China, using RFID and sensor systems to provide real-time data on waste. Hong et al.'s smart garbage system, implemented in Seoul's Gangnam district, showed average waste reductions of 33%. Both systems have shown positive effects on waste management across the value chain.

Intelligent Lunch Lines

A study by Koivunen et al. (2020) revealed that cafeterias worldwide struggle to balance ingredient production and customer demand, leading to an abundance of FW. They, together with a university and industry partners developed an innovative solution to reduce FW in their cafeterias. The solution was an intelligent self-serve lunch line equipped with sensors that collected data on customers' eating habits, preferences, and bio-waste generation. The data was then analysed to improve cafeteria operations and influence customer behaviour towards reducing FW. The study highlighted two major ways to reduce FW at lunch cafeterias: behaviour change interventions for customers and food production chain optimisation. The Hevner design science method was used to implement the line, which contained sensors tracking the FW of individual customers and displayed this data to customers via a dedicated mobile app. The data collected helped cafeteria staff identify the most commonly wasted food types and make adjustments to menu planning and production accordingly. The intelligent self-serve lunch line is a promising solution to reduce FW in cafeterias by collecting data on customers' eating habits and preferences, tracking bio-waste generation, and encouraging customers to be more mindful of their food choices (Koivunen et al., 2020).

Tracking Leftovers

Cheng and Leong (2023) developed an AI-powered plate waste tracker which automatically captures and analyses leftovers, providing invaluable insights into which foods are wasted and why. With this data, chefs can refine recipes, adjust portioning, and optimise menus for minimal waste. A staggering 20% reduction in plate waste was observed in a Macau resort (Cheng & Leong, 2023), benefiting the environment by reducing greenhouse gas emissions and resource consumption while generating financial savings for the resort.

AI-Powered Predictive Analytics Tools

By analysing data, AI algorithms can predict consumer demand, optimise inventory management, and reduce overproduction, thereby minimising waste across the entire supply chain (Onyeaka et al., 2023).

Optimising Restaurant Inventory

Efficient inventory management plays a crucial role in a business's profitability. When a business under-stocks, it fails to meet the demand leading to poor customer satisfaction and lower profits. On the other hand, over-stocking causes waste of raw materials and increased costs in inventory management (Mihirsen et al., 2020). To address this issue, Mihirsen et al. (2020) developed an ML system that uses algorithms such as Holt Winter's method and Seasonal and Trend decomposition to predict the quantity of raw materials needed to prepare dishes by forecasting their sales over a fixed period. The researchers conducted two surveys to measure the impact of under- or over-stocking on restaurants. One survey focused on the responses of customers when their preferred dishes were unavailable, while the other looked at the effects of excess or shortfall of raw materials on selected restaurants. By analysing the sales data of various dishes, the researchers found that every dish has its own sales trend and seasonality. This model utilises sales forecasts for each dish to determine the required raw materials. Additionally, this model can make seasonal suggestions if the appropriate data is available.

The study demonstrated the potential of ML to improve customer satisfaction and restaurant profit and optimise supply chain management. Mihirsen et al. (2020) discovered that 20-40% excess or deficit of raw materials affects half of a restaurant's profit, and one-third of customers are less likely to revisit a restaurant if their preferred dish is unavailable.

AI-Powered Ingredient Planning

According to Arvindaraj et al. (2023), estimating the necessary ingredients for food items in a menu list can help caterers save costs, reduce computational and manual calculation time, and minimise FW. The study proposes using AI techniques, specifically focusing on ingredient planning, to achieve these benefits. They suggested an AI-powered mobile application called the Ingredient Planner, which can assist customers and caterers by providing a list of ingredients required for selected food items. The results indicated that among the various techniques examined, AI-based ML is the most suitable for displaying the Ingredient Planner. This is because it can merge previous data with consumer food preferences and the variety of ingredients on display to provide the most relevant information for the given food item. Moreover, AI-based applications are used to find food ingredients and to make recipe recommendations (Morol et al., 2022). They presented a CNN model for recognising food ingredients and a recipe recommendation algorithm based on detected ingredients. The model achieved a 94% accuracy in testing and was particularly suitable for food ingredient recognition and developed a unique algorithm for recipe recommendations.

AI-Powered Raw Material Requirement Prediction

A widely used approach in reducing FW is forecasting sales to prevent overproduction. However, Harshini et al. (2021) argued that this strategy alone is insufficient. Food waste can arise not only due to overcooking but also due to the spoilage of raw materials (Harshini et al., 2021). As a result, various AI tools have been developed to predict demand and reduce FW. One such tool is the demand forecasting system for restaurants proposed by Harshini et al. (2021). This system incorporated a stacking technique that predicts the number of customers, sales for specific dishes, and raw material consumption.

Prediction of raw materials was a unique approach studied here. The model predicted the daily requirement of perishable goods and monthly requirement of non-perishable goods enabling restaurants to purchase the exact quantity of raw materials. The model's predictions for raw materials were almost the same or slightly higher than the actual values, indicating that it can be relied on to avoid raw material shortages. Although the forecasted values were occasionally lower than the original values, the model demonstrated the potential to reduce FW by providing optimal cooking and raw material procurement strategies for the restaurant. Therefore, this approach can be a valuable tool for businesses to improve their operations and reduce FW, thus, benefiting the environment and the bottom line.

AI-Powered Food Freshness Prediction

One-third of food is wasted due to expired best-before dates (Schmidt et al., 2019). Machine learning can help reduce FW by improving predictions on food packaging. Wunderlich et al. (2023) combined low-cost sensors and ML techniques to predict spoilage in fresh pizza. According to the research, volatile organic compounds (VOC) data is the most important and precise information for deciding how long fresh pizza can be stored. Various regression models such as linear regression, RF regression, and XGBoost regression can be used to predict spoilage and shelf life. If a gas sensor is used with an RF or extreme gradient boosting regressor, it can predict the day of spoilage with greater accuracy, which is a more cost-effective and precise alternative to the current methods. However, the approach is limited by controlled conditions and the complexity of food products. To improve the model's effectiveness, additional information should be collected during different stages of the food's life cycle, such as transportation or consumption. Improving these aspects can lead to more sustainable and accurate food freshness predictions.

Machine Learning for Pandemic Resilience

The research work of Malefors et al. in 2019 highlighted the potential of using AI-powered tools to reduce FW in public catering establishments during a pandemic. The study aimed to analyse the attendance of guests in Swedish catering establishments, including schools and preschools, both before and during the pandemic. To predict future guest attendance, an ML approach was used, and the results showed that the RF approach was effective in avoiding over-catering. The study recommended the use of forecasting tools to avoid overproduction, which can be adjusted during the first few days of restrictions by shifting the focus to handling overproduction. Overall, the study highlighted the potential of AI-related tools and other technologies in managing FW in public catering establishments, contributing to a more sustainable food system.

Machine Learning-Driven Demand Forecasting

Estimating the amount of food required to be produced is a challenging task, particularly in university restaurants due to the unpredictable behaviour of students and the numerous variables that need to be considered. However, recent studies have shown that ML methods can help solve this problem (Santos et al., 2021). Researchers conducted a study at a restaurant and tested three different ML algorithms, namely KNN, RF, and Artificial Neural Networks (ANN), to estimate the amount of food required. They analysed, pre-processed the data, and compared the results with human prediction and an algorithm that uses the average as an estimator. The study found that in three out of four scenarios, the ML algorithms outperformed the human prediction and the algorithm that does not use ML. However, in one scenario, human prediction performed better than ML algorithms (Santos et al., 2021). These results demonstrate that ML algorithms can be a useful tool in reducing FW in college restaurants. By forecasting the amount of food needed more accurately, universities can reduce FW and save resources.

Faezirad et al. (2021), and Aci and Yergok (2023) tackled the uncertainty inherent in student behaviour in university dining systems by predicting actual demand, a crucial step in minimising waste. Faezirad et al. (2021) proposed a model that predicted both deterministic and random components of demand by analysing student reservation patterns and segments alongside the crucial show/no-show rate. Their two-step prediction approach with ANNs addressed uncertainty in actual demand, leading to a remarkable 79% reduction in FW in their case study university. Aci and Yergok (2023) focused on high-demand, short-timeframe settings, such as lunch breaks, and demonstrated the superiority of Decision Tree-based methods for such contexts.

Both studies highlight the need for incorporating uncertainty into demand prediction models for effective FW reduction. However, some contradictory findings exist. A study by Li et al. (2019) found that the accuracy of demand prediction models varied depending on the type of food service and time of day. They suggested that combining ML algorithms and human expertise can lead to more accurate demand predictions. In conclusion, AI-powered demand prediction has transformative potential in combating FW within university dining systems. By embracing uncertainty through innovative model design and cost optimisation, these studies pave the way for a more sustainable future for university catering services and contribute significantly to the broader fight against FW.

AI-Driven Menu Design

Uğur Genç et al. (2019) discovered that there are certain food items that customers tend to order more frequently than others. This can pose a challenge for restaurants as they need to ensure that they have all the necessary ingredients in stock. However, through AI and ML algorithms, it is feasible to develop adaptive technologies that assist customers in making more informed decisions. The researchers devised an intelligent menu design capable of gathering data on available stock ingredients and promoting specific menu items or adjusting their prices to minimise spoilage and wastage. This menu is designed to direct customers toward dishes that utilise readily available ingredients to reduce waste. Moreover, the menu could offer recommendations for complementary dishes to decrease FW.

Real-Time Food Waste Monitoring

Zingg et al. (2021) have created an innovative IoT-based system for monitoring FW. The system captured images, recorded the weight of FW in commercial kitchens, and used

ML to analyse the data. The customers (restaurants and canteens) could access a summary of the collected information through an online dashboard. This allowed them to track their FW over time and make informed decisions to reduce it. By using ML directly on the embedded device, the system offers numerous advantages and has great potential due to the widespread deployment of embedded devices. In addition, running the ML algorithms directly on the embedded system enabled real-time data processing. It also enhanced privacy as only the results and not the raw data were sent to the cloud. This reduced the required bandwidth.

AI-Generated Key Performance Indicators (KPIs)

Amaro et al. (2021) conducted a study on FW in private and public collective catering units served by a Portuguese catering company. The study aimed to develop tools that can aid in waste control and operational planning of catering units by analysing data. To achieve their objectives, the team designed a set of KPIs to characterise FW over time. These indicators were evaluated based on various representations to create an intuitive and easy-to-understand dashboard for FW. The suggested approach took into consideration balancing the specifics of the generated data model with the related data creation and display, as standard practices call for straightforward, unbiased, repeatable, and cost-effective data-gathering methods. The proposed indicators and dashboard were tested for four weeks across six catering units, and the results were validated by the organisation. The study concluded that the proposed solution was beneficial and could help waste control and operational planning of catering units. This study provided a valuable contribution to the ongoing efforts to reduce FW in catering units (Amaro et al., 2021).

AI-Powered Demand Forecasting

A staff cafeteria in a Macau resort has implemented an innovative three-pronged approach that leverages cutting-edge AI technology. The approach, developed by Cheng and Leong (2023), demonstrated promising results within the broader FW literature. The first prong of the approach focused on upstream optimisation. With AI-powered demand forecasting models, chefs could tailor food preparation based on historical data and guest numbers, resulting in a significant reduction of upstream waste. This aligned with similar successful applications in hospitality settings (Paparisto et al., 2019; Sonesson et al., 2012).

AI-Powered Inventory Management

AI-powered inventory systems can optimise stock levels, reduce food spoilage, and improve supply chain efficiency, resulting in resource savings and waste reduction (Onyeaka et al., 2023).

Data-Driven Decision-Making in Food Pantries

University food pantries, in particular, often struggle with inventory management, leading to FW and inefficient use of resources. A recent study by Ufot et al. (2021) proposed an innovative solution to this challenge; an inventory tracking system that uses the Model-View-Controller (MVC) framework and data visualisation tools. The system collected real-time data on food inventory and generated visual figures for analysis. This helped pantry staff make more informed decisions about inventory management. By analysing past food donation and distribution patterns, the system could predict future client food choices and optimise inventory levels, thereby reducing waste. They highlighted the benefits of data visualisation in simplifying complex data, enhancing memory performance, and fostering business understanding among staff. By prioritising essential food preferences over unhealthy options, the system offered a promising direction for these pantries to adopt. This further displayed the potential of technology and data-driven insights in tackling FW within this resource-limited setting.

AI-Driven Substitution Model

In-flight catering creates excessive FW, with at least 20% of cabin waste comprising untouched meals (IATA, 2020), which poses a significant sustainability challenge. Unlike typical catering, its high production rates, off-site preparation, long lead times, and time-sensitive deliveries create unique difficulties. Addressing this, van der Walt and Bean (2022) proposed a novel multi-objective inventory decision-making model for in-flight caterers. They considered both the conflicting objectives of minimising waste and maximising passenger satisfaction. Their stochastic, mixed-integer programming model incorporated passenger load uncertainty through a time-inhomogeneous Markov Chain and multiple regression forecasting while introducing static product substitution. Compared to models lacking either element, incorporating both demonstrated their value. In other words, uncertainty inclusion boosted reliability in achieving minimum passenger satisfaction, while substitution reduced waste at a slight reliability cost.

Artificial Intelligence for Consumer Awareness and Education

AI-based apps and platforms can educate consumers by providing personalised tips on meal planning, proper storage, and innovative methods to minimise FW at home (Onyeaka et al., 2023).

Zhao and Dai (2023) conducted a study to explore the factors that contribute to FW in higher education institutions using the support vector machine model to classify waste in college cafeterias. The study then used the Probit Regression Model to identify the factors that cause FW. The study by Zhao and Dai (2023) found that FW is significantly linked to personal characteristics, family background, food conservation promotion, and dining habits.

Christine and Latifah (2022) conducted a study that used the Analytic Hierarchy Process method to evaluate the effectiveness of FW reduction strategies. Their findings suggested that raising awareness of FW, improving the management of canteens, and promoting sustainable consumption behaviours were effective strategies for reducing FW in university canteens.

The second prong of Cheng and Leong's 2023 approach introduced carbon and nutrition labelling on dishes to enhance guests' understanding of the environmental and health impacts of their food choices. Additionally, a custom-built nutrient-tracking website enabled diners to personalise their selections based on individual needs and environmental preferences. These empowered patrons through knowledge and echoed the findings by Principato et al. (2018). Cheng and Leong (2023) further stress that FW reduction is not just about leftovers, it is a systemic shift towards mindful consumption.

Artificial Intelligence-Based Donations and Redistribution

AI-powered food redistribution can reduce FW and insecurity by increasing food access to at-risk individuals and vulnerable communities (Onyeaka et al., 2023). By matching food donors with organisations, AI ensures donations are distributed to the most needy areas, reducing FW. Artificial intelligence can also improve food access, affordability, and stability for vulnerable populations. Furthermore, it can improve the efficiency of food distribution systems by analysing data and identifying safe food items. AI-powered distribution promotes sustainability by ensuring efficient distribution and reducing FW, potentially diverting food from landfills (Onyeaka et al., 2023).

In 2021, Varghese et al. developed a mobile application named SeVa. The app aims to reduce FW by reusing available food sources in local communities. Through this app, users could visualise the food resources available, thereby reducing hunger and FW. The app uses principles from AI, particularly Human-Computer Interaction, and is unique in its functionality. The SeVa app is designed to facilitate food donation by providing a user-friendly interface that offers relevant food information for suppliers and consumers. It aims to address the COVID-19 food crisis and contribute towards achieving the UN Sustainable Development Goals related to hunger, poverty, and healthcare. Feedback received from survey participants suggests that the prototype SeVa app was well-received and useful during the COVID-19 pandemic and its aftermath.

Zhou et al. (2021) developed a software application that leveraged AI to locate specific items for users to request. This application enables volunteers to pick up resources from food pantries and deliver them directly to individuals' homes, increasing the frequency at which families receive quality groceries. The application was tested to enhance the accessibility and reach of food pantries through volunteer involvement. The results showed a significant decrease in FW after the application was implemented, demonstrating its immediate effect on increasing the usage of food pantry resources. Moreover, the application benefited restaurants and grocery stores by reducing their FW and carbon footprint by bringing surplus food to food pantries and families experiencing food insecurity.

In summary, the literature collectively emphasises the various approaches and technologies used to comprehend and tackle FW in different scenarios. From ML algorithms to image processing and digital tools, these studies contribute valuable insights and solutions to the ongoing dialogue on sustainable practices in the hospitality industry.

Challenges in AI Implementation for Food Waste Reduction

Adoption of AI in the hospitality industry faces challenges, despite its potential benefits. The following section explores challenges associated with AI's implementation in the hospitality sector.

Data Challenges

Accurately collecting and managing diverse data points across kitchen operations, customer preferences, and inventory can be complex and costly. Studies note the need for reliable data collection systems and integration across different sources (Mihirsen et al., 2020; Ufot et al., 2021). Data quality is crucial for effective AI models, requiring robust data cleaning and validation processes (Cheng & Leong, 2023).

Furthermore, concerns exist around data privacy, especially regarding customer behaviour and food consumption patterns. Eriksson et al. (2019) highlighted the importance of transparency and user consent when collecting and utilising such data. Implementing robust data security measures is essential to gain trust and comply with regulations (Malefors et al., 2021).

Technological Challenges

Implementing AI solutions often requires upfront investment in technology, training, and infrastructure, which might be prohibitive for smaller businesses (van der Walt & Bean, 2022). Striking a balance between cost and potential benefits is crucial. Mihirsen et al. (2020) suggested exploring open-source AI tools and leveraging cloud-based solutions to reduce initial costs. Prediction models face challenges, such as high technology costs, and large data sets (Wunderlich et al., 2023).

Integrating AI solutions with existing inventory management and operational systems can be complex and require technical expertise (Faezirad et al., 2021). Seamless integration ensures smooth data flow and avoids compatibility issues. Ufot et al. (2021) emphasised the need for standardised data formats and APIs to facilitate efficient integration. Embedded systems have limited resources, such as memory or CPU power. Therefore, the ML algorithms must be optimised for the embedded system (Zingg et al., 2021).

Artificial intelligence algorithms have inherited biases from the data they are trained on, potentially leading to inaccurate predictions or unfair practices. Zhao and Dai (2023) suggested employing diverse datasets and implementing fairness-aware metrics during model development to mitigate this risk.

Human and Organisational Challenges

Implementing AI often requires staff training and adaptation to new processes and technologies (Aci & Yergok, 2023). Effective change management strategies are crucial to ensure employee buy-in and successful adoption. Mihirsen et al. (2020) recommended involving staff in the implementation process and providing ongoing training and support.

Limited awareness among some businesses about the benefits and capabilities of AI in FW reduction can hinder adoption (Eriksson et al., 2019). Educational initiatives and knowledge sharing are essential to bridge this gap. Ufot et al. (2021) suggested industry collaborations and pilot projects to display the potential of AI solutions.

Systemic Issues

Davis et al. (2020) found that FW reduction interventions that focus solely on data analysis might overlook broader systemic issues related to food access and distribution. Therefore, while data-driven tools are useful in reducing FW, they should be used in conjunction with broader efforts to address the root causes of food insecurity and waste.

Briefly, AI has the potential to revolutionise the food industry by optimising food production and supply chains, reducing waste, and redistributing excess food to those in need. In fact, according to Onyeaka et al. (2023), AI can help create a more sustainable and equitable food system by maximising resource efficiency and minimising environmental impact. However, despite its potential benefits, AI faces several challenges in its development, deployment, and utilisation, hindering its widespread adoption and the realisation of its full potential. These challenges include issues related to data privacy, transparency, and ethical concerns (Rodrigues, 2020). There is also a need to ensure that AI is accessible and affordable for all stakeholders in the food industry, regardless of their size or location (Ladd, 2023).

To sum up, AI has the potential to transform the food industry by making it more sustainable, efficient, and equitable. However, its adoption requires careful consideration of the challenges and limitations that it presents.

Food Waste, Artificial Intelligence and Sustainability

The hospitality industry is increasingly becoming aware of the impact of FW on the environment and the importance of implementing sustainable practices. According to Chisnall (2017), 97% of businesses surveyed recognised the significance of both financial and environmental outcomes as motivators for reducing FW. Environmental concerns were acknowledged by approximately 75% of businesses.

The trend towards sustainability is further supported by research conducted by Booking.com (2022), which revealed that around 70% of global travellers prefer eco-friendly hospitality brands. This highlights the need for hoteliers and culinary managers to adopt a more sustainable approach to FW management.

By implementing effective waste management practices, businesses can reduce their expenditures and enhance their brand reputation by demonstrating their commitment to environmental sustainability and corporate social responsibility. This positive trend towards sustainability and responsible business practices is encouraging and should be supported by the industry (Lee & Huang, 2023).

Several studies have investigated the use of technology in the hospitality sector to combat climate change and promote sustainability. One study by Wen et al. (2018) examined the use of IoT network technology to manage restaurant FW in Suzhou, China. The study found that this technology positively affected waste management. Youssef and Zeqiri (2022) conducted a literature review on the implementation of Industry 4.0 in the hospitality sector. They identified several conditions under which Industry 4.0 technologies can contribute to sustainability, including enhancing energy efficiency, reducing water consumption, minimising FW, and promoting Circular Hospitality 4.0. These technologies can achieve the objectives of the Paris Agreement by reducing greenhouse gas emissions and promoting sustainable development. Nadkarni et al. (2023) further emphasised the importance of technological advancements in achieving a sustainable business model in the hospitality sector. Collectively, the studies suggest that AI-driven technologies can optimise resource utilisation, reduce waste, and contribute to sustainable development when integrated into hospitality operations.

By harnessing the power of intelligent algorithms and data analysis, the hospitality industry can unlock innovative solutions to tackle FW thereby contributing to SDGs.

Examples of AI Applications Used in the Hospitality Industry

AI-powered waste tracking systems are aiding businesses in identifying waste sources and implementing effective solutions. The following section captures some of the applications used in the industry to tackle FW.

Winnow - Winnow technology automates the recognition and measurement of FW, recording and weighing unconsumed products by categories, such as expired stock, leftover buffets, cooking errors, peelings, and plate returns. It provides detailed information on waste by ingredient or recipe, enabling hotels to measure its weight, value, and environmental and financial impact. In 2020, 56 hotels used the Winnow-connected smart scale, resulting in a 56% reduction in FW. For example, Sofitel in Kunming China, using the Winnow system, reduced FW by over 50%, saving over USD 19,000 and avoiding 20 tonnes of CO2 emissions (Hotel Technology News, 2023).

Principato et al. (2023) analysed FW in a company canteen using the Winnow platform powered by advanced ML algorithms. This ground-breaking research shed light on the immense potential of AI in tackling this global challenge. Employing a longitudinal approach with data from 2018 and 2019, the researchers leveraged sophisticated ML models such as Boosting, RF, and Bagging to analyse daily FW quantities. These algorithms acted as powerful detectives, unveiling key factors associated with waste generation and enabling targeted interventions in the kitchen and consumer behaviour.

Orbisk - Orbisk is an innovative waste management system for the hospitality industry. It uses AI technology to monitor and predict FW and associated CO2 emissions. A camera is installed above a waste bin, which recognises discarded products. This data is then compiled into actionable insights that help the user identify areas of waste and implement changes to reduce it. By making adjustments to portion sizes, stocking, and planning, food service companies can save significant amounts of money while reducing FW (Hotel Technology News, 2023).

Gaïa - Accor, a leading hospitality company, has developed a specialised online reporting tool called Gaïa, which enables its properties to measure their waste accurately and adhere to shared standards. Gaïa makes it easier for hotels to monitor their energy, water, waste, and carbon footprint performance, enabling them to track the impact of their sustainability initiatives. This technology-based solution is unique to Accor hotels and helps them to be sustainable (Hotel Technology News, 2023).

Fullsoon. Fullsoon, implemented at Accor, estimates the number of customers, the dishes that will be ordered, and the exact quantity of ingredients required to prepare them. This application optimises food and beverage margins and reduces waste.

Lumitics - Lumitics employs AI, sensors, and CV to monitor and categorise FW. The information gathered is analysed and displayed in a format that identifies areas where portion sizes can be decreased. Additionally, the data reveals unpopular dishes that may need to be substituted. Ultimately, this technology offers valuable insights to assist businesses in minimising FW (Hotel Technology News, 2023).

Kitro - Martin-Rios et al. (2020) carried out an in-depth case analysis investigating a start-up offering automated technology-based AI tools, Kitro, designed for quantifying FW. It reported that the average reduction of AFW in canteens, hotels and restaurants was 20-50%, 25-60% and 15-40% respectively. Kitro is an IoT-based solution for FW management that uses a combination of hardware and software. The hardware includes a camera and scale to capture images of waste bin contents, which record when new waste is disposed of. The software recognises both unavoidable and AFW, allowing for systematically analysing returned plates and making adjustments. Kitro also uses ML to classify food items based on images and physical weight changes. The analysis is presented in an online dashboard, allowing restaurant owners and chefs to make data-driven decisions, leading to more resource-efficient processes and significantly reducing FW and cost (Martin-Rios et al., 2020).

Research Gaps

Based on the literature review, this study has identified several research gaps that can be strengthened and focused on in future research. Firstly, despite the hospitality sector facing a significant challenge in reducing FW, there is limited academic literature on this topic, which is concerning (Dhir et al., 2020; Filimonau and De Coteau, 2019). Impetus needs to be given to research in the area (Dhir et al., 2020) and there is a need to understand the determinants of effective mitigation (Filimonau et al., 2018; Tomaszewska et al., 2021). Secondly, there is some significant literature in the context of New Zealand, but most of the relatively recent studies have been focused on varied aspects of FW, such as retail FW (Goodman-Smith et al., 2020; Goodman-Smith et al., 2021), household FW (Reynolds et al., 2016) behaviour (Sharp et al., 2021) food security (Mannette, 2020), restaurant FW (Chisnall, 2018; Jones, 2018; Mainvill et al., 2018; WasteMINZ, 2018), municipal solid waste (Munir et al., 2021), and sustainability (Mills et al., 2023). Undoubtedly, the research on the hospitality industry, particularly in New Zealand, needs further exploration.

The literature review discusses several studies on the potential of AI to reduce FW in the hospitality sector. However, there is a lack of research specifically focusing on the New Zealand hospitality industry, indicating the need for further investigation. In pursuit of addressing this research gap, the study aims to evaluate how AI can effectively reduce FW within the hospitality industry in New Zealand.

The hospitality industry is largely lacking in sophisticated FW management and potential AI applications, as noted by Martin-Rios et al. (2020) and Palm (2023). For instance, future advancements could involve AI cloud connections to suppliers, accurate supply-demand coordination, analysis of sales data and customer preferences, and inventory optimisation through demand, seasonality, and supplier lead times (Mouysset, 2023; Palm, 2023). Although it has not been explored, it is outside the scope of the study.

While some studies have investigated consumers' attitudes towards AI in the hospitality industry (Roy et al., 2020), there is a lack of research that focuses on the perceptions and attitudes of stakeholders in the hospitality industry. Therefore, this research aims to explore the potential of AI in reducing waste and promoting sustainability in the New Zealand hospitality industry. It aims to bridge the gap between knowledge and perceptions of AI in the hospitality sector. It is crucial to evaluate the readiness of the industry to adopt AI solutions, given the significant FW management challenges faced by New Zealand.

In terms of the originality of this study, it can be highlighted that this research is unique in its focus on exploring the role of AI in reducing FW and enhancing sustainability within the hospitality industry in New Zealand. While several studies have explored the issue of FW in the hospitality industry in New Zealand, this study contributes to the literature by specifically focusing on the potential of AI-powered solutions for FW reduction in the hospitality industry of New Zealand. Additionally, this study takes a comprehensive approach by exploring the knowledge, applicability, and perception of key stakeholders towards AI-powered solutions for FW reduction. Therefore, this research contributes to the literature by providing a unique perspective on the potential of AI for enhancing sustainability in the hospitality industry.

Summarised below are the strengths, weaknesses and research gaps of the literature.

Table 1

Evaluation of Literature

Aspect	Strengths	Weaknesses	Research Gaps
Hospitality (General)	• Identifies FW as a significant challenge (Dhir et al., 2020; Filimonau, 2019).	• Limited research on FW in the hospitality industry (Dhir et al., 2020; Filimonau and De Coteau, 2019) • Limited understanding of FW determinants (Filimonau et al., 2018; Tomaszewska et al., 2021).	• Need further research on FW in the hospitality industry and research on effective FW mitigation strategies in the industry (Dhir et al., 2020).
Hospitality (New Zealand)	• Some research on FW in New Zealand hospitality (Chisnall, 2017; Jones, 2017; WasteMINZ, 2018).	• Existing research focuses on various aspects (retail FW, household FW) (Goodman-Smith et al., 2020). • Existing research on FW in New Zealand hospitality is limited to restaurants and cafes and focuses primarily on quantifying FW (Chisnall, 2017; Jones, 2017; WasteMINZ, 2018).	• More research is needed to understand FW in the NZ hospitality industry
AI Potential (General)	• Highlights AI's potential for FW reduction in hospitality (Martin-Rios et al., 2020).	• Unexplored AI applications exist (Martin-Rios et al., 2020; Palm, 2023).	• Explore sophisticated AI applications in hospitality for FW reduction (Martin-Rios et al., 2020) and beyond (Palm, 2023).
AI Potential (New Zealand)		• No studies have been conducted on the use of AI to decrease FW in the New Zealand hospitality industry.	• Investigate the efficacy of AI for FW reduction in New Zealand hospitality
Stakeholder Perception	• Attitudes of consumers towards the use of AI in different industries (Roy et al., 2020)	• Lack of research on knowledge, perceptions and readiness for AI for FW in the hospitality industry	• Bridge the knowledge gap on AI and assess hospitality industry readiness for AI for FW • Explore stakeholder perceptions of AI for FW reduction in the hospitality industry

Summary

This chapter has explored the use of AI in the hospitality industry to reduce FW and achieve sustainability. Reducing FW can reduce greenhouse gas emissions, lower food costs, and enhance the hospitality industry's reputation. AI-powered systems can track food inventory, optimise production, and reduce spoilage and preparation waste. These systems use predictive analytics and ML algorithms to analyse data and forecast demand, predicting high-demand items and waste. This helps chefs and restaurant managers adjust production, reduce unsold food, and minimise waste. Artificial intelligence can also identify patterns in FW, such as frequent waste, returned dishes, and unpopular items, enabling chefs to adjust recipes, reduce waste, and enhance customer satisfaction. The chapter provided a comprehensive analysis of AI's potential for FW reduction in the hospitality industry.

This study is unique in its focus on AI's role in reducing FW and enhancing sustainability in the New Zealand hospitality industry. It contributes to the literature by examining the potential of AI-powered solutions for FW reduction. The research also explores the knowledge, applicability, and perception of key stakeholders towards AI-powered solutions for FW reduction. This comprehensive approach provides a unique perspective on the potential of AI for enhancing sustainability in the hospitality industry in New Zealand.

Chapter 3 - Research Methodology

This chapter outlines the methodological approach designed to investigate the potential of AI in reducing FW within the New Zealand hospitality industry. A structured survey was conducted to gather data from industry stakeholders, focusing on the current state of FW, knowledge, perceptions, and attitudes of stakeholders. The mixed-methods approach was used, combining qualitative and quantitative methods. Analytical techniques included descriptive statistics and thematic analysis. Ethical considerations were duly considered, with informed consent obtained from participants and confidentiality ensured. The research was conducted following the Ethics Committee guidelines.

Research Design Procedure

Research design is an essential part of a study. It defines the framework and approach to gathering data. Many interrelated decisions need to be made, and the research approach is one of the most important decisions (Sileyew, 2019). The research procedure is illustrated in Figure 1, and details are discussed in relevant sections.

Figure 1

Research Design Procedure Flow Chart Sileyew (2019), page 28, Figure 1. CC By 3.0

redacted

https://books.google.co.nz/books?hl=en&lr=&id=eqf8DwAAQBAJ&oi=fnd&pg=PA27&dq=Sileyew+2019+research+design+procedure&ots=cLN40Wa9U9&sig=oUYEqLYrW05i3yeEowHL-9NroOM#v=onepage&q=Sileyew%202019%20research%20design%20procedure&f=false

Research Approach

Leedy and Ormrod (2016) define the research methodology as the overall approach taken by a researcher, which may influence the tools they use in their research project. The three methods of conducting research are quantitative, qualitative, and mixed methods (C. Williams, 2007). The primary research approach for this study was quantitative. Quantitative research examines the variables of interest, often measured numerically using commonly accepted physical measures or carefully designed psychological measures such as tests, questionnaires, or rating scales, to understand their relationships and behaviours (Leedy & Ormrod, 2016). This approach is well-suited for investigating the prevalence of AI knowledge, current FW management practices, and overall perceptions of AI's potential in reducing FW within the hospitality sector.

The research also incorporated a qualitative element. Leedy and Ormrod (2016) emphasise the importance of qualitative research in understanding the depth and complexities of a specific phenomenon. Often it involves in-depth perspectives from people about a particular issue, rather than reducing it to numerical values. By including open-ended questions in the survey, the research aimed to capture in-depth insights regarding the challenges and opportunities associated with implementing AI solutions for FW reduction. Thematic analysis techniques were employed to identify recurring themes and patterns within the participants' responses.

This combined approach allowed not only to see what is happening (quantitative) but also to understand why and how it is happening (qualitative), leading to a more comprehensive understanding of the research questions.

Research Paradigm

This research used a positivist paradigm, emphasising objectivity and the scientific method, to investigate the potential of AI in reducing FW in the New Zealand hospitality sector. By collecting quantitative data on FW, AI awareness, and perceptions of AI for FW reduction, the research aimed to establish the current state of the issue and assess the potential impact of AI solutions. The positivist approach allows for the collection of generalisable findings through a structured survey (Park et al., 2020), enabling the research to make broader inferences about the hospitality industry as a whole. The positivist emphasis on standardised methods facilitated replication and objectivity, contributing to a strong body of knowledge on AI and FW reduction.

The research also acknowledged the importance of incorporating interpretivist elements, such as understanding the meaning and interpretation of phenomena from the perspective of the individuals involved (Chowdhury, 2014). This is relevant for the successful implementation of AI solutions, as open-ended questions capture subjective experiences and potential concerns. The research also acknowledged that the effectiveness of AI solutions may vary depending on the specific context of a hospitality business, potentially including questions about business size, type, and location. By adopting a mixed-methods approach, the research leveraged the strengths of both positivism and interpretivism, allowing for a more comprehensive investigation of the research questions.

Research Instrument

The primary research instrument for this study was a self-administered online questionnaire developed using the Qualtrics software (refer to Appendix 4). Online surveys offer several advantages, including cost-effectiveness, ease of administration, and the ability to reach a geographically dispersed population (Wright, 2017). Additionally, some studies suggest that online surveys are as effective as face-to-face interviews (Gosling et al., 2004).

The questionnaire was designed to be user-friendly and accessible on various devices (mobiles and laptops) and methods (online link, QR code or a hard copy). The questions were developed in such a way that participants answered questions based on their selections, for instance, if a participant's response was 'no' to the question 'Have you heard of or experienced any AI technologies specifically designed to reduce FW in the hospitality industry?', they were automatically directed to the question 'What methods are used to minimise FW in your establishment?' avoiding the question 'What are some examples of AI technologies you have heard of or experienced?'. This enhanced relevance, and effectiveness and was time-saving.

To ensure the effectiveness of the survey, a pilot testing phase was carried out to identify any potential issues, such as missing or ambiguous questions that could affect the quality of the data collected. Once the pilot testing was completed, the final version of the survey was distributed to the participants. Several approaches were used to access the participants for the survey. These included; walk-ins, contacts, mailing the questionnaires, posters on company notice boards, and emailing. Additionally, participants were accessed via LinkedIn, which helped reach a targeted wider population for the research. To ensure the quality of the data collected, a data management plan was created to organise and clean the data before analysis. The data was first cleaned to remove any incomplete or invalid responses. Once the data was cleaned, it was organised and stored in a secure database for analysis. The data management plan ensured the accuracy and reliability of the data and assisted in the analysis of the results.

The questionnaire was divided into the following sections. The demographic section collected basic information about respondents, such as age, gender, and work experience in the hospitality industry. In addition, information about the establishment they work in, such as the type of establishment, location and size. The FW and causes section attempted to understand the level and causes of current FW in the respective establishments. Knowledge and awareness of the AI section assessed participants' knowledge and understanding of AI technology. The perceptions of AI for the FW reduction section attempted to gauge participants' perceptions of the potential benefits and challenges of using AI solutions to reduce FW. Participants' intentions of implementation of AI were captured in the succeeding section. The sustainability goals section assessed the motivations of the hospitality companies in achieving sustainability goals. Open-ended questions were included to gather qualitative data on participants' experiences with AI.

Research Sampling

In line with the practical considerations outlined in Chisnall's study in 2017, a convenience sampling approach was adopted in addition to the snowball sampling technique. Convenience sampling is a data collection method used by researchers to gather data from an easily accessible population. It differs from probability and non-probability sampling, as it requires researchers to visit public locations and ask passersby to participate. This method applies to almost any research but is only used when participant availability is a concern and when researchers cannot select from multiple populations or research sites. This technique may be criticised for selection bias due to the difference in the target population (Golzar et al., 2022). The time-sensitive nature and the geographical dispersion of the New Zealand hospitality industry make this approach suitable.

To reach a wider audience within these regions, snowball sampling was also employed. Snowball sampling involves recruiting participants through existing networks and asking them to refer colleagues or acquaintances who might be interested in participating (Atkinson & Flint, 2001). This technique was used to help reach geographically dispersed participants. Geographical-based selection strategy was used in Chisnall's 2017 research to capture the diverse distinctions of New Zealand's hospitality landscape.

Research Respondents

The research under consideration aimed at studying the knowledge, attitudes and perceptions of individuals working or having previously worked in the New Zealand hospitality industry. Respondents with hospitality sector experience in New Zealand were allowed to complete the questionnaire for targeted participation.

In the research study conducted by Chisnall (2017), a sample size of 150 participants was chosen from a total of 250 New Zealand café and restaurant businesses that were randomly selected. A convenience sampling methodology was later adopted to increase the participation rate and data quality. The study mirrored the sample size determination based on Chisnall's 2017 study. Although the sample size of the study may seem small compared to the total number of outlets in the industry, it was justified in several ways. Firstly, the sample size consisted of individuals from diverse roles in the industry, including owners, managers, chefs, sustainability managers, wait staff, and kitchen staff, among others. This ensured that the study was representative of the industry as a whole and provided a comprehensive understanding of the issues at hand. Secondly, the sample size was appropriate for the research question and also manageable in terms of data collection and analysis. Finally, the practical limitations of previous studies, including Chisnall's 2017 study, were taken into account in the sample designing process. Overall, the steps taken to justify the sample size ensured that the study was reliable.

The selection of establishments was based on the classification of Australia New Zealand Standard Industrial Classification, and all sizes of organisations, from small to large were accessed. This approach was adopted to ensure that the sample represented a wide range of establishments with varying levels of resources and capabilities to manage FW and implement AI. The focus on individuals with direct experience within the hospitality sector allowed collection of data from knowledgeable informants with a practical understanding of FW challenges and potential solutions.

Potential bias and limitations in sampling and survey responses can impact the validity and reliability of research findings. These biases can arise due to several reasons such as non-response bias, selection bias, and measurement bias (Leedy & Ormrod, 2016). Non-response bias can occur when a significant proportion of the selected sample does not respond to the survey. This can lead to a biased sample that does not accurately represent the target population. Similarly, selection bias can occur when the sample is not representative of the target population due to the chosen sampling method. For example, if a researcher only surveys people from a particular region, the findings may not apply to the larger population. Measurement bias can arise when the survey instrument is not designed well, or when the respondents provide answers that are influenced by social desirability bias or other factors.

To minimise these biases, several steps were taken in the research study. Convenience sampling and snowball sampling methods may introduce some bias into the sample, as individuals who are more readily available or have more extensive social networks may be overrepresented. However, it is worth noting that these sampling methods can still be useful in certain situations, such as when the target population is difficult to reach, for instance, hospitality professionals in the South Island, or when a preliminary exploration of a topic is required. To address any potential biases introduced by these sampling methods, efforts were made to recruit a diverse group of participants and to increase the response rate through strategies such as sending reminders and using multiple modes of communication. The survey instrument was also designed carefully, and the questions were pilot-tested to ensure that they were unambiguous.

Overall, while it was impossible to eliminate all bias and limitations in research, the steps taken in this study helped minimise these biases and increase the validity and reliability of the findings.

Validation of Instrument

To ensure the accuracy and reliability of the survey used in the study, several steps were taken. First, the survey was developed based on a thorough review of existing literature on FW reduction in the hospitality industry and the use of AI for sustainability. The questions were designed to align with the research aims and objectives and to elicit meaningful responses from participants. Next, a pilot study was conducted with a small group of participants who were representative of the target population. The responses were analysed for clarity, relevance, and consistency, and adjustments were made to the survey as necessary. The final survey was then reviewed by the research supervisor and a panel of experts in the Ethics Committee. Their feedback was incorporated into the survey to ensure that it was valid, reliable, and free from bias. Finally, the survey was administered to a large and diverse group of participants, and the responses were analysed using statistical software to ensure that the data was accurate and reliable. Any responses that were incomplete or inconsistent were removed from the analysis to ensure data quality. Overall, these steps helped to ensure that the survey used in the study was accurate, reliable, and fit for purpose.

Selection of Articles for Literature Review

The study utilised Scopus, a reputable database, to select studies for review, searching for keywords such as the following:

(TITLE-ABS-KEY ("food waste*" OR "edibles waste*") AND TITLE-ABS-KEY ("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "AI solutions" OR "AI applications" OR "AI technology" OR "integration of AI" OR "AI implementation" OR "AI adoption" OR "innovations in AI" OR "food waste management" OR "AI-driven food waste technologies" OR "computer vision" OR "data visualisation") AND NOT TITLE-ABS-KEY (agri-food) AND NOT TITLE-ABS-KEY (waste AND management)) AND (LIMIT-TO (SRCTYPE, "j") OR LIMIT-TO (SRCTYPE, "p") OR LIMIT-TO (SRCTYPE, "k") OR LIMIT-TO (SRCTYPE, "b"))

A search on Scopus yielded 595 studies, including journal articles, conference papers, book chapters, reviews, editorials, and letters. Out of these, 455 were excluded as they were not directly related to AI solutions for FW in the supply chain. To understand AI solutions, 119 articles were reviewed, and only the most relevant were shortlisted for further analysis. Twenty-one studies related to AI for FW in the hospitality sector were selected and analysed in detail.

Data Analysis

Quantitative and qualitative data require distinct research methods and analysis strategies (Leedy & Ormrod, 2016). Quantitative researchers use deductive reasoning to draw logical conclusions from hypotheses and maintain objectivity, while qualitative researchers use inductive reasoning to make specific observations and inferences about larger phenomena. Both types of reasoning are used in a continual, cyclical fashion, with quantitative researchers formulating preliminary theories through inductive reasoning and qualitative researchers identifying themes in their data using inductive processes (Leedy & Ormrod, 2016).

Primary Data Analysis

Quantitative data collected from the online survey were analysed using MS Excel. Descriptive statistics, including frequencies, and percentages, were used to summarise the data and identify trends regarding AI awareness, waste management practices, and perceptions of AI for FW reduction. Qualitative data from open-ended questions were analysed using thematic analysis techniques. This process involved identifying recurring themes and patterns within the responses to better understand participant perspectives (Braun & Clarke, 2006).

Secondary Data Analysis

In addition to the primary data collected through the online survey, the research also incorporated secondary data analysis. This involved utilising existing data sources relevant to the research topic. Secondary data can provide valuable context and background information to supplement the primary data analysis. Industry reports such as the Restaurant Association of New Zealand provided insights into the current state of FW in the New Zealand hospitality sector, prevailing waste management practices, and emerging trends. Government statistics were used to capture definitions, guidelines and statistics such as the Ministry for Environment, which were used to benchmark against the findings from the primary research. Academic journal articles and conference proceedings related to AI applications in FW reduction and hospitality industry practices provided valuable theoretical frameworks and case studies to inform the research analysis. Hence, the research utilised secondary data analysis alongside primary data analysis to enhance the strength of its findings.

Ethical Considerations

This study aimed to understand AI's role in reducing FW in New Zealand's hospitality sector, adhering to ethical standards. An anonymous online survey was conducted, with demographic questions included, and participants were able to skip or decline to answer these. Cultural sensitivity and Māori principles were respected if anyone was selected from the Māori population. Data were securely stored on Google accounts and external backup storage, with retention for seven years in compliance with Otago Polytechnic's policy. Participation was voluntary, and potential respondents were enlightened about the global significance of addressing FW issues. After completion, participants will receive a copy of the research, if they so wish. Otago Polytechnic's Research Ethics Committee provided ethical approval and oversight (Reference Number: AIC-RE-2023-14. Please see Appendix 5), and any potential ethical concerns were promptly addressed in consultation.

Addressing Research Gaps with the Survey and Methodology

This study's methodology, particularly the survey design, directly tackles the research gaps identified in the literature review. Table 2 below captures the salient features of the survey and methodology.

Table 2

Reviewing Survey and Methodology

Aspect	Description
Focus on New Zealand Hospitality	The survey targeted individuals with experience working in the New Zealand hospitality industry. This directly addressed the gap of limited research on FW in this specific context.
AI for NZ Hospitality	The survey assessed participants' knowledge, perceptions, and potential implementation intentions regarding AI for FW reduction. This directly targeted the gap of no existing studies on AI for FW reduction in NZ hospitality.
Stakeholder Perception	By including questions on knowledge, perceptions, and intentions regarding AI for FW reduction, the survey aimed to understand stakeholder perspectives within the New Zealand hospitality industry. This addressed the gap of the lack of research on industry perceptions of AI for FW.

Overall, the survey design and mixed-methods approach directly address the research gaps by focusing on the New Zealand hospitality industry and capturing stakeholder perspectives on AI for FW reduction. The inclusion of secondary data analysis strengthens the research by providing a broader context for the findings.

Summary

This chapter has outlined the research methodology designed to investigate the potential of AI in reducing FW within the New Zealand hospitality sector. The research employed a mixed-methods approach, combining quantitative and qualitative data collection methods to gain a comprehensive understanding of the industry's dynamics and stakeholder perspectives. The research adhered to a positivist paradigm with a focus on objective measurement while acknowledging the importance of interpreting subjective experiences through open-ended questions. The research instrument was a self-administered online survey targeting individuals with experience working in the hospitality industry in New Zealand. Data analysis involved a combination of quantitative and qualitative techniques, along with the utilisation of secondary data sources. Finally, the research was committed to upholding ethical principles throughout the research process.

Chapter 4- Data Analysis and Findings

In this chapter, descriptive analyses and thematic analyses are presented, which were conducted on the data collected from the survey on the role of AI in reducing FW in the hospitality industry in New Zealand. The analysis examined quantitative and qualitative data from closed-ended and open-ended questions. Chapter 3 provided an overview of the analysis techniques used throughout the analysis process. The use of these techniques helped to ensure that the analysis was both comprehensive and systematic. Overall, this chapter provides the research findings on the causes of FW. Moreover, it provides the knowledge, perceptions and experiences of hospitality industry professionals regarding using AI to reduce FW and evaluate the organisations' broader sustainability goals.

The Survey

This study aimed to gather data from hospitality employees in New Zealand, focusing on obtaining a sample representative of the industry's roles, experience, and organisational types. A sample size of 150 was sought, however, 134 hospitality professionals working or having worked in the hospitality industry in New Zealand responded to the survey, and three were excluded based on specific criteria. This resulted in a reduced sample size of 131 participants for data analysis. It is worth noting that not all questions were mandatory, leading to variations in the sample size for each question. This is indicated explicitly in the discussion where relevant.

The survey was divided into seven sections for analysis. The first section focused on participant demographics, and the second section examined their work establishments. The third section aimed to understand the reasons for FW, and the following three sections (four, five, and six) aimed to explore stakeholders' knowledge, perceptions, and attitudes within the hospitality industry regarding the integration of AI for FW reduction. The survey also sought to understand how these perceptions influenced AI adoption and its effectiveness. Finally, the seventh section assessed the broader sustainability goals within these organisations.

Section 1- The Demographics of the Participants

Before exploring the results, the demographic characteristics of the respondents were scrutinised. Understanding the participants' demographics is important in any study, as it allows researchers to gain insights into the population's characteristics (Kelley et al., 2003). In this study, demographic analysis was conducted to determine the age, gender, work experience, and occupation of the participants. The results provide valuable information for the interpretation of the findings and for making generalisations about the population.

Moreover, analysing demographics is important in studies related to sustainability, as it allows researchers to identify patterns and differences in perceptions and behaviours across different demographic groups (Sargisson et al., 2020). Therefore, by analysing demographics, researchers can better understand the factors that shape individuals' perceptions and behaviours related to FW and sustainability.

Explored in section one of the questionnaire were the respondents' age, gender, occupation and years of service in the hospitality industry. A snapshot of the salient statistics is presented in Table 3 below and discussed in detail in the subsequent sections.

Table 3

Salient Demographic Characteristics of the Sample

Baseline Characteristic	N	%
Gender		
Male	82	63%
Female	46	35%
Other	1	1%
Prefer not to say	2	2%
Age		
Under 25	24	18%
25-34	44	34%
35-44	39	30%
45-54	19	15%
55 and Older	5	4%
Occupation		
Owner/Manager	29	22%
Chef/Cook	23	18%
Food Service Manager	16	12%

Baseline Characteristic	N	%
Sustainability Manager	3	2%
Wait Staff	25	19%
Kitchen Staff	15	12%
Other	19	15%
Experience		
Less than 2 Years	44	34%
2-5 Years	29	22%
6-10 Years	19	15%
More than 10 Years	39	30%

Note. *N* (number) =131 except in occupation *N* = 130

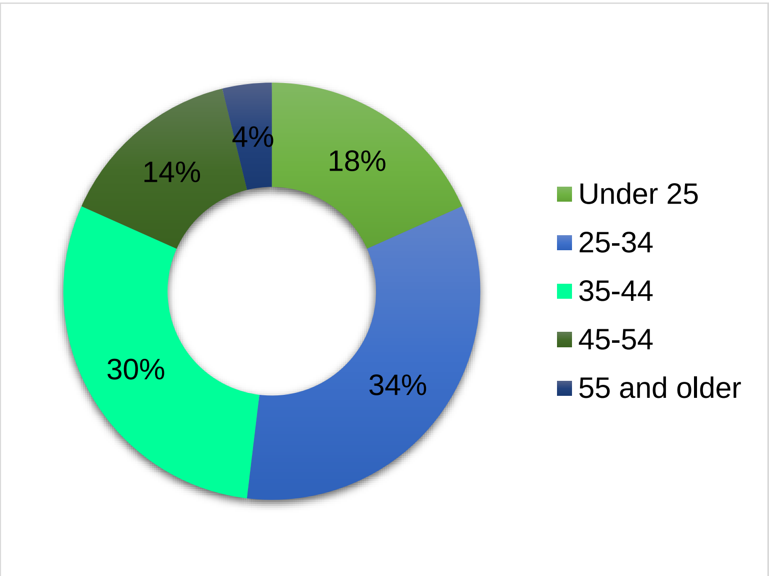
The following sections analysed in detail the demographic profile of the sample; the characteristics of individuals and the organisations. A demographic profile is important in research as it helps researchers identify and understand the factors that may influence the outcomes of the study.

Distribution by Age

Age often influences a person's knowledge and experience regarding a particular topic or subject and may influence openness to new technology. Figure 2 below depicts the age distribution of the survey participants grouped into five age groups.

Figure 2

Age Distribution of Respondents



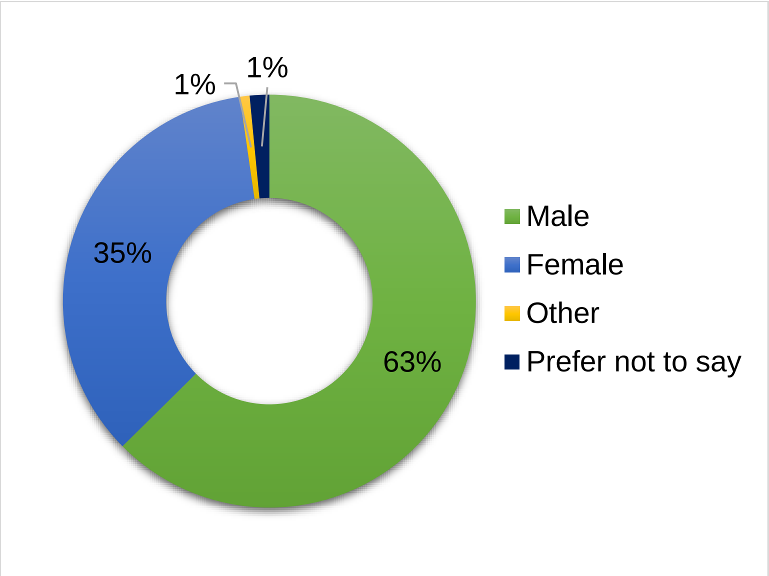
The majority of the participants (34%) were aged between 25 to 34 years, followed by those aged between 35 and 44 years (30%). The below 25 years and the 45 to 54 age groups accounted for 18% and 14% respectively. The over-55 age group constituted the smallest group, comprising only 4% of the sample. Interestingly, the hospitality sector appears to have a younger workforce compared to the national workforce average. Analysis of detailed industry-level Census 2018 data by Infometrics indicates that over half (51%) of all hospitality sector workers are below the age of 30 years. This may also be due to the nature of the work itself, which often involves part-time, casual, and temporary work (Fletcher & Rasmussen, 2020). The survey results are well-aligned with the national workforce age profile.

Distribution by Gender

The questionnaire was designed to cater to a gender-diverse environment by incorporating categories beyond traditional male and female categories. Participants who chose not to disclose their gender identity were allowed to indicate their preference not to say. Figure 3 below depicts the gender distribution of the survey participants.

Figure 3

Distribution by Gender



As depicted in Figure 3 above, almost two-thirds of the participants have identified as male and the balance largely comprises females. A small percentage is represented by the other and prefer not to say categories. The hospitality industry workforce in New Zealand has however traditionally been made up of more female workers as per MBIE (2022).

The breakdown of gender by job role of the sample is tabulated in Table 4 below.

Table 4

Occupation by Gender

Gender	Occupation/Role in the Establishment					
	Owner/ Manager	Chef/Cook	Food Service Manager	Sustaina bility Manager	Wait Staff	Kitchen Staff
Male	26%	22%	15%	4%	17%	15%
Female	25%	19%	11%	0%	36%	8%

Based on Table 4, it can be observed that males occupy more senior roles in the hospitality industry as compared to females. The data shows that 26% of males are owners/managers of the establishment, while only 25% of females hold that position. Similarly, 22% of male chefs/cooks are male, whereas only 19% are female. It is also evident that males represent a higher percentage of the food service manager and sustainability manager positions, while females represent a higher percentage of the wait staff (36% vs 17%) positions.

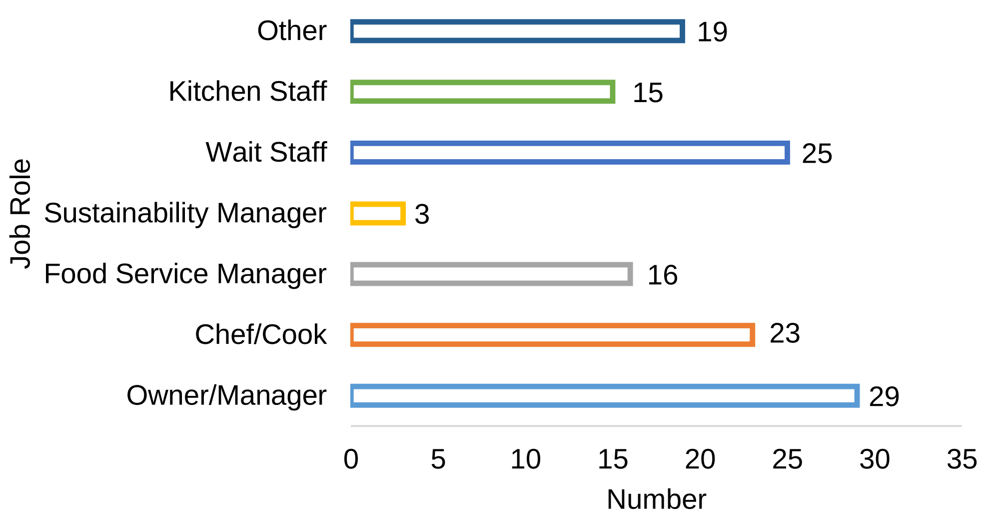
Baum's 2013 report on women working in hotels, catering, and tourism revealed that women were predominantly employed in lower-level occupations such as waiters, while men were employed in more senior (e.g. senior kitchen staff) and managerial roles. This survey reflects this phenomenon (e.g. composition of wait staff). Moreover, according to StatsNZ (2020), the number of women working in key tourism industries (including accommodation cafes and restaurants) dropped more than 8 percent in the June 2020 quarter, compared with the previous year. Lastly, the survey incorporated measures beyond these categories to obtain a sample which was representative of the industry in terms of roles, experience, and organisational types among others.

Participants' Role in the Establishment

Job analysis is important for identifying the necessary knowledge, skills, and expertise for effective job performance. In addition, different roles have varying levels of decision-making power for AI adoption. The study probed into various roles directly linked to FW management at both operational and strategic levels. Figure 4 below depicts the distribution of the survey participants by job role.

Figure 4

Distribution by Job Role



The majority of the respondents were owners/managers (22%) followed by wait staff (19%), chefs/cooks (18%), others (15%), food service managers and kitchen staff (12% each). Sustainability managers have the least representation at 2%. It was expected that most of the respondents to this survey would be owners and managers, as their perceptions of AI solutions adoption are crucial. The 'other' category included roles such as duty manager, operations manager, front office staff, executives, among others. The majority of respondents did not identify their assigned roles in this category, which was a disadvantage in the analysis process.

Table 5 below captures the roles in the organisations across different age groups. Different age groups may have varying levels of experience with technology and openness to adopting AI solutions. In addition, it could provide information on decision-making power regarding AI implementation.

Table 5

Employee Age Vs Role in the Organisation

	Age Category				
Occupation	Below 25	25-34	35-44	45-54	55 and older
Owner/Manager	1	10	7	8	3
Chef/Cook	1	9	8	5	0
Food Service Manager	2	7	5	1	1
Sustainability Manager	0	0	1	2	0
Wait staff	9	11	4	1	0
Kitchen staff	7	2	5	0	1
Other	4	4	9	2	0

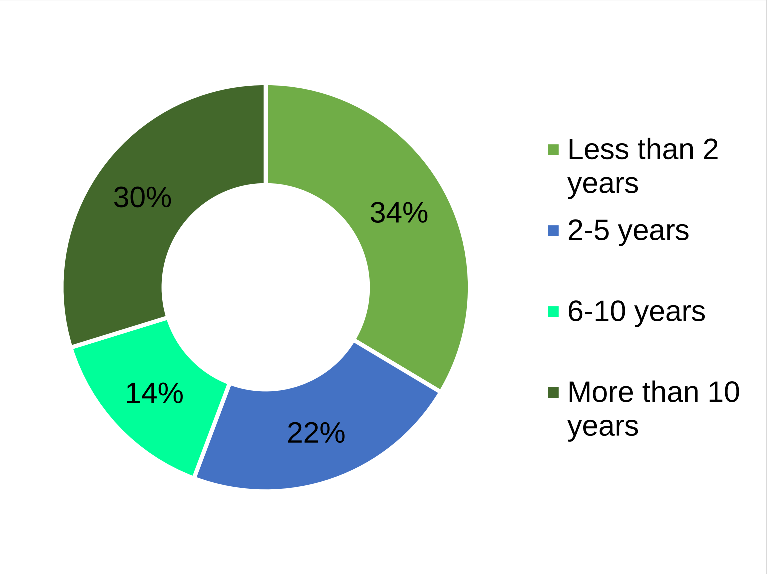
Most managerial roles are held by individuals over 25, with only 7% of managerial positions held by those under 25 years old. Over two-thirds of these roles are lower level, such as wait staff. The hospitality industry may favour young individuals in less skilled roles such as wait staff, contrasting with roles based on specialisation or experienced hierarchy (e.g. chefs).

Experience in the Hospitality Industry

Figure 6 below depicts the number of years of experience of the survey participants in the hospitality industry in New Zealand. Experience may play a crucial role in determining the acceptance of AI, either positively or negatively. More experienced staff may have a wealth of practical experience in FW reduction techniques that can be valuable when combined with AI.

Figure 5

Number of Years of Experience in the Hospitality Industry



According to the survey results, 34% of respondents have less than 2 years of experience, while 30% have over 10 years of experience. The remaining 36% of respondents are split between the 2 to 5-year bracket (22%) and the 6 to 10-year bracket (14%). The wait staff category has the most employees with less than 2 years of experience, followed by Owner/Manager with 18 employees over 10 years, and Chef/Cook and Food Service Manager with a significant number of employees over 10 years. This diverse range of experience is a valuable factor in understanding the industry's perceptions of AI adoption.

Section 2- Understanding the Nature of the Organisation

Section two of the questionnaire aimed to capture the organisations' nature, location size, and number of years the organisation has been in operation. These are factors which may influence the decision to implement AI technologies.

Type of Organisation

Table 6 displays the organisation type of the survey participants. The type of establishment provides insights into the nature of FW, its sector-specific causes and the strategies implemented to mitigate it.

Table 6

Type of Establishment

Establishment	N	%
Fine Dining Restaurant	17	13%
Casual Dining Restaurant	24	19%
Fast Food Restaurant	22	17%
Hotel/Resort	32	25%
Catering Service	5	4%
Café/Coffee Shop	16	12%
Pub, Tavern or a Bar	2	2%
Hospitality Club	-	0%
Other	11	9%
	129	

The majority of the respondents were from hotels/resorts (25%), followed by casual dining restaurants (19%), fast food outlets (17%), fine dining restaurants (13%) and cafes/coffee shops (12%). The 'Other' category which accounted for 9% of the total respondents, includes motels, event management organisations and bakeries. Some participants have not provided information on the type of organisation in their responses. This, however, has no significant impact on the survey results. Catering services and pubs, taverns or bars accounted for 4% and 2%, respectively. There were no responses from hospitality clubs. As per the statistics published in the Hospitality Report 2018, just above one-half of the market share in the hospitality industry was enjoyed by cafes and restaurants, followed by fast food restaurants (27.1%), pubs and bars (13.4%), catering (5.7%) and clubs (2.8%). This study revealed that fine dining and casual dining restaurants and hotels collectively account for over half of the market share, reflecting the current market distribution.

Location of the Establishment

Table 7 below analyses the responses by location. Location is an important factor that indicates the concentration of market share and market dynamics. Regional variations in food supply chains, customer preferences, and access to technology/facilities may be different across the North and the South Islands or within the two islands.

Table 7

Location of the Establishment

Location	N	%
Auckland	102	80%
Canterbury	3	2%
Wellington	12	9%
Waikato	2	2%
Rest of North Island	1	1%
Otago	1	1%
Bay of Plenty	2	2%
Rest of South Island	4	3%
Manawatu-Wanganui	1	1%
	128	

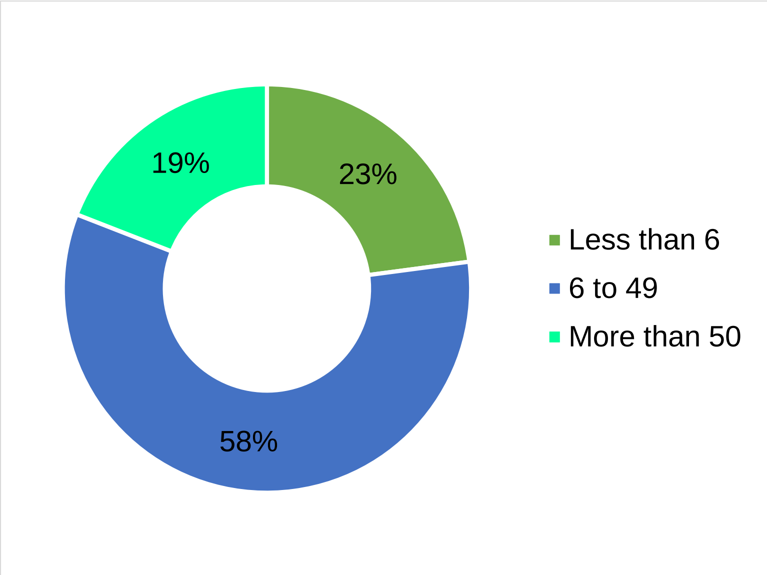
The table displays a highly skewed distribution, with 80% of respondents from Auckland and the remaining 14% and 7% from the rest of the North Island and South Island respectively. As per the number of outlets published by the Restaurant Association of New Zealand in their report of 2018, almost 40% of the outlets were situated in Auckland followed by Canterbury (12.5%) and Wellington (10.8%). The market share of the South Island is approximately 20%.

Number of Employees in the Organisation

Figure 6 below depicts the number of employees in the organisations, an indication of the size of the organisations. The size of an organisation significantly influences culture, strategic decision-making, and resource allocation, all of which affect the adoption of technology within the organisation.

Figure 6

Number of Employees in the Establishments



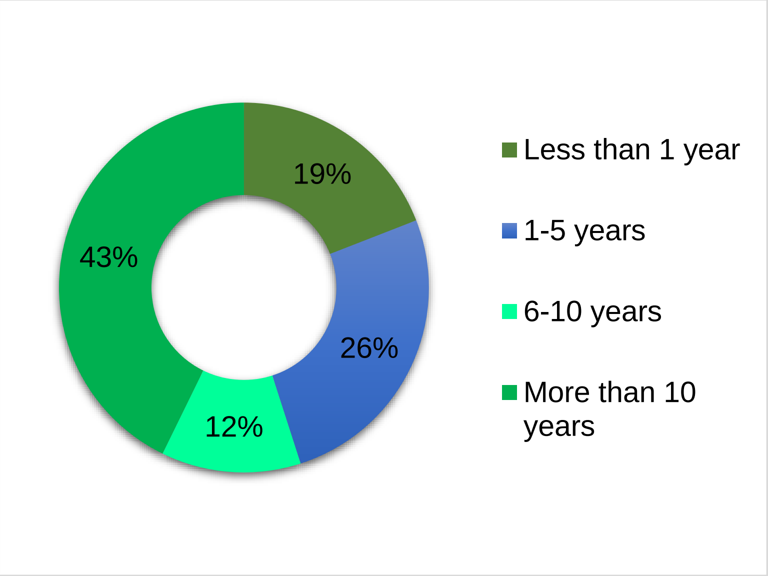
More than one-half (58%) of the organisations fall into the small and medium category, followed by the micro-enterprises category which accounted for 23% of the sample. According to Figure NZ (2024), of enterprises in the accommodation and food services industry in New Zealand by employee count, 68% accounted for micro-enterprises and 30% for small and medium enterprises (SMEs). Less than 2% comprised large organisations in the industry. It should be noted that definitions vary according to various sources. Within the hospitality sector, SMEs (less than 20 employees) represent 92% of all establishments (Tibay et al., 2018).

Number of Years in Operation

Figure 7 below shows the experience of the organisations in the industry measured in terms of the number of years in operation. The number of years of experience in the hospitality industry could provide valuable insights regarding the role of AI in reducing FW. For example, organisations with more years of experience may have a better understanding of the challenges and opportunities related to FW reduction. By collecting data on the size and experience of different organisations, a better understanding of how AI can be effectively implemented in the hospitality industry to reduce FW could be assessed.

Figure 7

Years in Operation



A majority of the organisations (43%) have more than 10 years of experience in the industry. This suggests a mature segment within the industry. Organisations with 1 to 5 years and 6 to 10 years are 26% and 12% respectively. Relatively new to the industry comprised 19% of the sample analysed.

In conclusion, analysing demographics is a crucial aspect of any study, as it provides valuable insights into the population's characteristics. In this study, the demographic analysis facilitated gaining a better understanding of the sample. Moreover, these findings suggest that the sample was diverse and representative of the population being studied.

Section 3- Food Waste and its Causes

The questionnaire's section three aimed to understand FW categories, AFW, and causes, although the main objective was not an in-depth analysis or quantification of FW, it provided a solid foundation for the study. Responses for each question in the section are presented below.

Question 1

"Over the last week, what percentage of the food in your establishment ended up as waste?"

Table 8 below captured the percentage of food that ended up as waste. Understanding FW quantification baselines is crucial for assessing its magnitude and hot spots, and provided a foundation for the study.

Table 8

Food Waste Categories

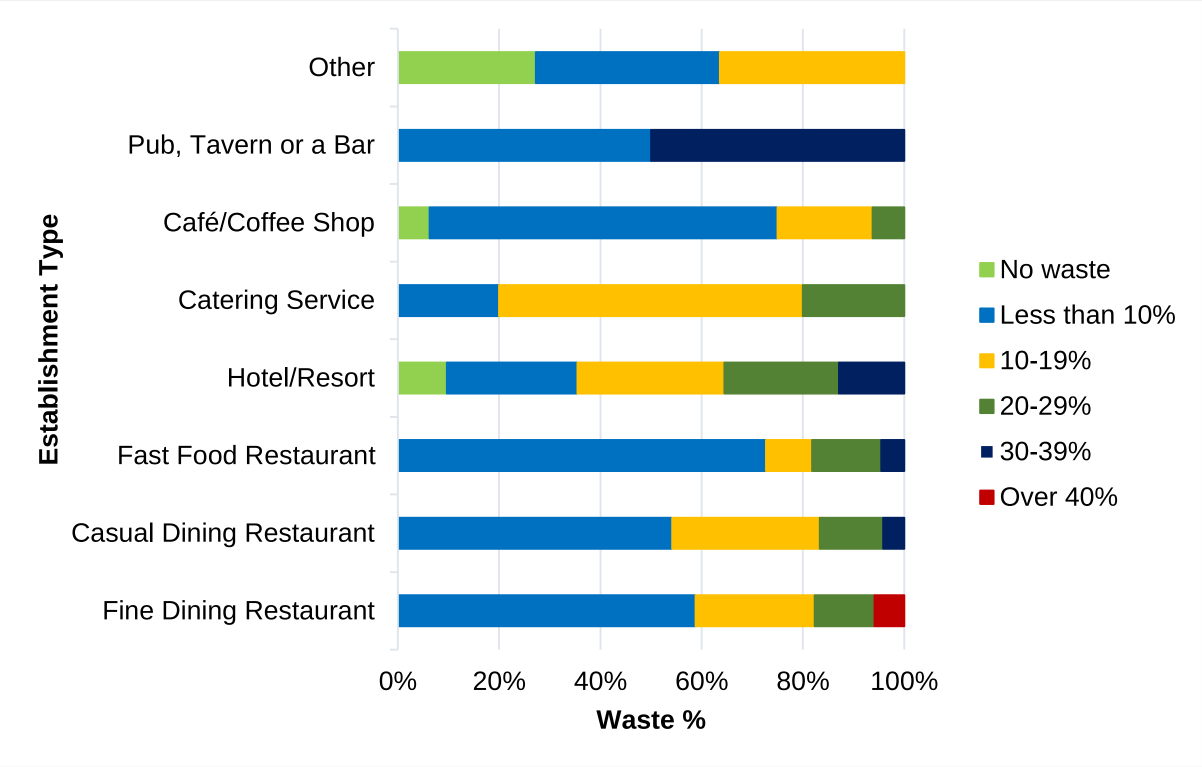
Category	N	%
Less than 10%	66	51%
10-19%	32	25%
20-29%	17	13%
30-39%	7	5%
Over 40%	1	1%
No Waste	7	5%
	130	

Approximately one-half of the respondents reported FW to be less than 10% and another quarter responded that FW is in the region of 10% to 19%. Overall, the data suggests that most of the sample's establishments are on the lower end of FW, with a small percentage experiencing high waste levels. Interestingly, 5% claim no waste. This could indicate successful waste reduction strategies or a lack of knowledge or methods to measure FW.

Figure 8 illustrates FW according to the sub-sectors of the industry. These data can help identify the nature of FW by establishment type, providing insights into targeted interventions to reduce FW.

Figure 8

Food Waste by Type of Establishment



Fine dining restaurants show a significant amount of waste in the 10% to 19% and 20% to 29% categories, with a notable 6% exceeding 40% of waste. Casual dining restaurants have a more even distribution across the lower waste categories, with a small percentage in the 30% to 39% range. Fast food restaurants are highly efficient, with 73% reporting less than 10% waste. Hotels/Resorts display a broad spread across all categories, with a higher tendency towards the 10% to 29% waste range. A majority of the catering services fall within the 10% to 19% waste category. Café/Coffee shops are quite efficient, with the majority reporting less than 10% waste. Half of the pubs, taverns or bars report less than 10% waste, while the other half report 30% to 39% waste (there were only 2 responses). Finally, the other category has a notable 27% reporting no waste, and an even distribution in the less than 10% and 10% to 19% categories. Two-thirds of participants failed to identify the establishment type in the 'other' category, making further analysis challenging.

Fine dining restaurants, and hotels in particular, may need to focus on waste reduction strategies given the higher percentages of waste reported.

Question 2

"Of the food waste generated in your establishment last week, what percentage could have been avoided? ('Avoided' refers to any edible food that was thrown away)"

Table 9 outlines the responses to the above question. To develop effective strategies for reducing AFW it is important to quantify it.

Table 9

Avoidable Food Waste Categories

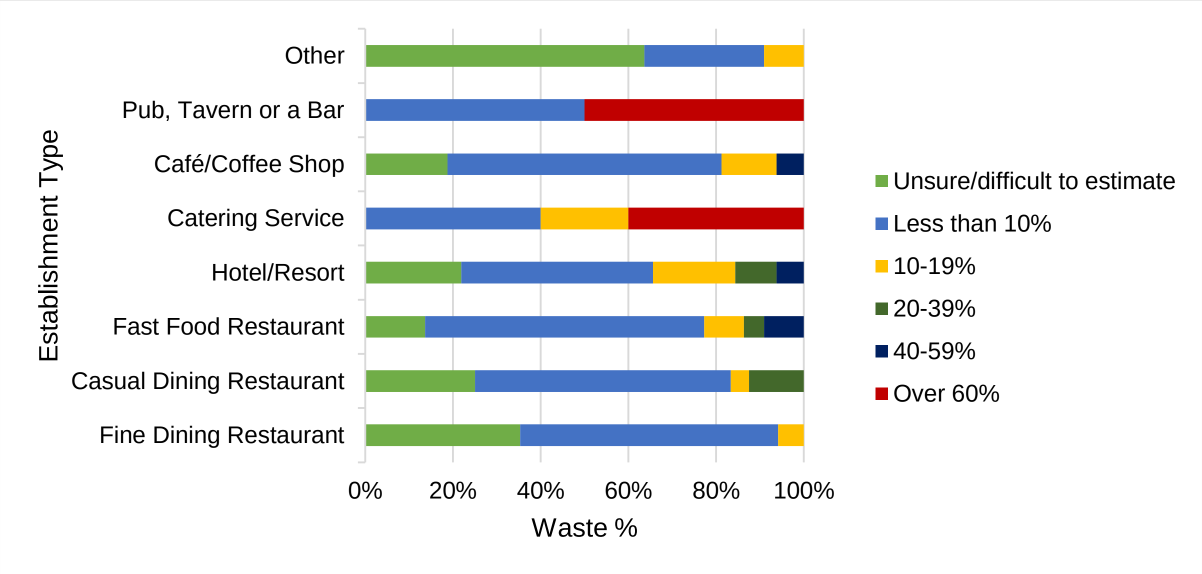
Category	N	%
Less than 10%	68	53%
10-19%	14	11%
20-39%	7	5%
40-59%	5	4%
Over 60%	3	2%
Unsure/Difficult to estimate	32	25%
	129	

The majority, 53% of the respondents, fall into the less than 10% category, indicating that most people estimate their AFW to be less than 10% of their total FW. A smaller group, 11% of respondents, estimate their AFW to be between 10% to 19%. Only 5% of respondents believe their AFW falls into the 20% to 39% category and 4% estimate their AFW to be between 40% to 59%. A minimal 2% of respondents estimate that more than 60% of their FW is avoidable. A significant 25% of respondents are unsure or find it difficult to estimate their AFW. This could indicate a lack of awareness or difficulty in estimating FW accurately.

Figure 9 below illustrates the AFW by type of organisation.

Figure 9

Avoidable Food Waste by Type of Establishment



A significant portion (35%) of the fine dining restaurants are unsure or unable to estimate their AFW, while a majority (59%) estimate less than 10% is avoidable. In casual dining restaurants, a quarter are unsure, with most (58%) estimating less than 10% avoidable waste. Less uncertainty (14%) is seen in fast food restaurants, with a majority (64%) estimating less than 10% AFW. Less than half (44%) estimating under 10% avoidable waste in hotels/resorts. A spread across 10% to 60% is observed. A stark division with 40% estimating less than 10% and another 40% over 60% AFW is seen in catering services. Café/Coffee Shops are similar to fast food, with 19% unsure and most (63%) estimating less than 10% AFW. Pubs, taverns or bars estimated over 60% AFW whilst the other category shows the highest uncertainty (64%), with 27% estimating less than 10% AFW.

This data suggests that perceptions of AFW vary significantly by establishment type. This could reflect operational differences, customer behaviour, or awareness levels regarding FW.

Question 3

"In your opinion, which of the following are the major contributors to food waste in your establishment?"

Reducing FW is a key strategy for improving sustainability, and identifying its causes is a fundamental aspect of this process. Survey participants were asked to rank the causes of FW on a scale of one to five. Participants were allowed to choose multiple causes and rate their severity on the scale. Salient features are captured below.

Table 10

Causes of Food Waste

Category	Rank (Frequency)				
	1	2	3	4	5
Inaccurate demand forecasting	23	21	27	22	17
Portion control and plate waste	26	12	24	23	26
Inefficient inventory management and storage	32	25	20	11	14
Lack of food waste awareness/training	26	24	21	15	20
Supply chain challenges	38	20	16	13	13
Other	15	2	5	4	11

Note. The ranking system ranks items from 1 to 5, from the least important cause (rank number 1) to the most important cause (rank number 5).

The table above provides an overview of various challenges faced by the hospitality industry in terms of; demand forecasting, portion control and plate waste, inefficient inventory and storage, lack of FW awareness/training, supply chain challenges, and other issues.

The frequency ranking for inaccurate demand forecasting is 22.0, with a standard deviation of 3.16, indicating a significant cause of FW across different categories. Low variability in frequency ranking across these categories suggests consistent identification of this issue as a contributing factor. Portion control and plate waste have a divided view, being seen as both a low and high cause of FW. Inefficient inventory management and storage is more tilted towards the lower end of the spectrum (32 at rank 1). The study found that lack of FW awareness/training is a significant cause of FW across the categories. The frequency ranking of this factor is 21.2, with a standard deviation of 3.92. The frequency ranking across categories shows low variability, indicating that lack of FW awareness/training is consistently identified as a cause of FW. Supply chain challenges are viewed by a majority as a low cause of FW (38 at rank 1), indicating it's not considered a significant factor.

Further analysis of FW's highest-ranked causes (frequencies under rank 5) by type of organisation, revealed the following results. The analysis proved important to understanding sub-sector-specific challenges which may help in focusing on high-impact areas and implementing initiatives to tackle the same.

Table 11

Greatest Causes of Food Waste Ranked by Type of Organisation

Cause	Fine Dining		Casual Dining		Fast Food		Hotels		Catering		Café		Pub		Other	
	frequency	*Rank*	frequency	*Rank*	Frequency	*Rank*	frequency	*Rank*	frequency	*Rank*	frequency	*Rank*	frequency	*Rank*	Frequency	*Rank*
Inaccurate demand forecasting	3	***3***	1	***2***	2	***2***	3	***4***	2	***1***	5	***1***	-	***-***	1	***3***
Portion control and plate waste	6	***1***	3	***1***	1	***3***	8	***2***	1	***2***	4	***2***	1	***1***	2	***2***
Inefficient inventory and storage	3	***3***	1	***2***	2	***2***	4	***3***	-	***-***	3	***3***	-	***-***	1	***3***
Lack of food waste awareness/ training	2	***4***	-	***-***	4	***1***	9	***1***	1	***2***	2	***4***	1	***1***	1	***3***
Supply chain challenges	4	***2***	1	***2***	2	***2***	2	***5***	-	***-***	3	***3***	-	***-***	1	***3***
Other	1	***5***	-	***-***	-	***-***	3	***4***	-	***-***	2	***4***	-	***-***	4	***1***

Table 11 shows the causes of FW ranked in order of importance by the type of organisation. For instance, portion control and plate waste were the number one cause in fine dining followed by supply chain challenges (e.g., due to sourcing premium ingredients) and inaccurate demand forecasting and inventory management. Inaccurate demand forecasting is the main cause of FW in catering services and cafes/coffee shops. Apart from fine dining restaurants, casual dining restaurants and pubs cited portion control and plate waste as the main cause of FW. Lack of FW awareness was the prime cause of FW in hotels/resorts and fast food outlets.

Overall, the table highlights the diverse range of challenges faced by the hospitality industry and provides insights into the areas where improvements can be made to increase efficiency, reduce waste, and enhance customer satisfaction.

Section 4 – Knowledge of AI-Driven Technologies for Food Waste Reduction

Understanding participants' existing knowledge of AI applications is crucial as it establishes a baseline for measuring the impact of the research. It may also influence perceptions of AI and its potential implementation in the industry.

This section investigated the AI knowledge of the participants specifically relating to FW reduction methodologies. In other words, how familiar are the participants with AI applications used in the hospitality industry to reduce FW? The study also attempted to understand what measures are currently adopted to tackle FW.

Question 1

"Have you heard of or experienced any AI technologies specifically designed to reduce food waste in the Hospitality Industry?"

The question attempted to gauge participants' overall familiarity with AI applications for FW reduction. Figure 10 below depicts the results as follows.

Figure 10

Overall Familiarity with Artificial Intelligent Applications in Food Waste

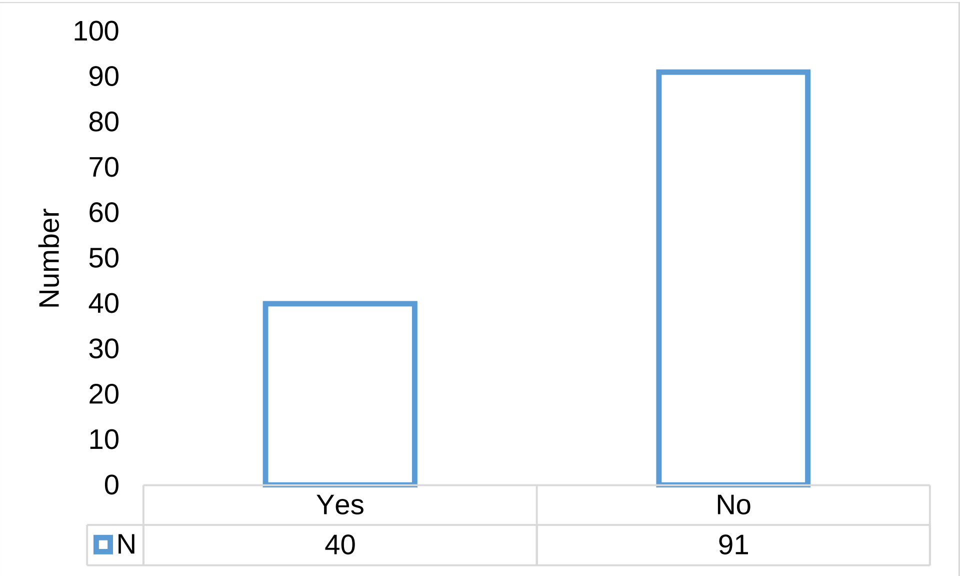


Figure 10 displays the responses received regarding the familiarity and non-familiarity of AI applications utilized in the hospitality sector. Nearly 70% of respondents in the hospitality industry have not heard of or experienced AI technologies being used to reduce FW, compared to 30% who have experienced or have heard of AI applications in their careers. This indicates a significant gap in the awareness and adoption of AI technologies within the hospitality industry.

Question 2

"If you selected yes, what are some examples of AI technologies that you have heard of or experienced being used in the hospitality industry to reduce food waste?"

The study aimed to gauge participants' familiarity with specific AI applications in the hospitality industry, asking them to rate these AI technologies in reducing FW. The responses ranged from 'not at all familiar' to 'very familiar', with responses listed below.

Table 12

Assessment of Familiarity with Artificial Intelligent Applications

AI technology	Not at all familiar	Moderately familiar	Very familiar
Sensors and devices that identify food spoilage (N=37)	10 *27%*	24 *65%*	3 *8%*
Using cameras to track food waste on plates (N=35)	10 *29%*	18 *51%*	7 *20%*
Intelligent kitchen management systems (N=37)	7 *19%*	21 *57%*	9 *24%*
Forecasting demand using machine learning (N=37)	7 *19%*	18 *49%*	12 *32%*
Smart bins that tell you how much food is wasted (N=37)	9 *24%*	19 *51%*	9 *24%*
Other	1	4	-

It appears that for sensors and devices that identify food spoilage, 27% of the participants are not familiar with it, while 65% are moderately familiar, and 8% are very familiar. When it comes to using cameras to track FW on plates, 29% of the participants are not familiar with it, while 51% are moderately familiar, and 20% are very familiar. For intelligent kitchen management systems, 19% of the participants are not familiar with it, while 57% are moderately familiar, and 24% are very familiar. Furthermore, for forecasting demand using ML, 19% of the participants are not familiar with it, while 49% are moderately familiar, and 32% are very familiar with it, making this application the most familiar out of all the applications stated in the questionnaire. Lastly, for smart bins that tell you how much food is wasted, 24% of the participants are not familiar with it, while 51% are moderately familiar, and 24% are very familiar. Among the responses in the 'other' category is that the respondent's organisation owns a specific-company AI application module.

Overall, the data suggests that there is moderate familiarity with AI technology among the participants. Additionally, there is a varying degree of familiarity with the different applications of AI in reducing FW. Based on the responses, it appears that the participants are more familiar with intelligent kitchen management systems and forecasting demand using ML, while they are less familiar with sensors and devices that identify food spoilage and smart bins.

Question 3

"If you selected no, what methods are used to minimise food waste in your establishment?"

If the participants were not familiar with AI applications for FW reduction they were directed to the above question. Responses are tabulated in Table 13 below.

Table 13

Other Methods Used for Food Waste Reduction

Other Methods	N	%
Implementing food waste tracking system/Food waste audits	36	17%
Altering menu choices/portions	51	25%
Composting/Donating surplus food	24	12%
Educating staff and customers about food waste	57	28%
Inventory management software	27	13%
Other	4	2%
None	7	3%

Educating staff and customers about FW was considered the most widely used method, followed by altering menu choices/portions. Composting/donating surplus food appears the least favoured method. 3% of the responses pertain to no method being applied whilst out of the four responses in the 'other' category three responses were that excess food is used for staff meals and manual monitoring of stocks. Portion control/plate waste and lack of FW awareness/training were cited as the most significant causes of FW (Table 6). It appears from the above results that many of the strategies are diverted towards tackling these two issues.

Section 5 – Perception towards Artificial Intelligence for Food Waste Reduction

The questionnaire aimed to gather participants' perceptions of AI for FW reduction, providing insights into potential challenges and opportunities for implementation in the hospitality industry.

Question 1

"Do you believe that AI technologies have the potential to reduce food waste in the Hospitality Industry significantly?"

The respondents were surveyed on their perception of AI's potential to significantly decrease FW in the hospitality industry, with results presented in Figure 11.

Figure 11

Perception towards Artificial Intelligence for Food Waste Reduction

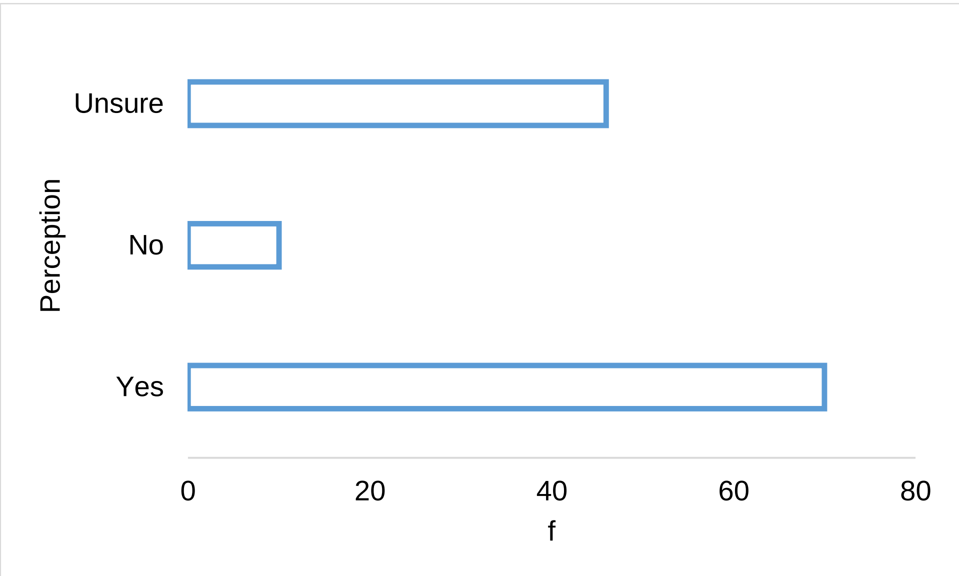


Figure 11 shows participants' perceptions of AI applications' potential to significantly reduce FW in the hospitality sector, indicating their agreement, disagreement, or uncertainty. The "Yes" category has the highest frequency (70), followed by "Unsure," (46) and "No" (8) has the least. This suggests that the majority of respondents have a positive perception or agreement with AI for FW reduction, while a smaller portion disagree. Interestingly, more than one-third of the participants were skeptical. Reasons for this are analysed in detail below.

Question 2

"If you selected yes, what excites you about the potential of AI tools for reducing food waste in the Hospitality Industry?"

Participants were asked about their belief in the potential of AI tools for FW reduction if they answered 'yes' to question one. The answers are tabulated as follows.

Table 14

Potential of Artificial Intelligent Tools for Reducing Food Waste

AI tool	N	Rank
Improved operational efficiency	50	2
Data-driven decision making	47	3
Real-time monitoring and alerts	38	4
Cost savings and enhanced revenue	52	1
Improved customer satisfaction	35	5
Other	3	6

Note. N =70

Table 14 outlines various ways in which AI tools can significantly reduce FW. Implementation of AI tools would bring in cost savings and improved revenue is ranked as the most effective followed by improved operational efficiency, data-driven decision-making, real-time monitoring and alerts, and improved customer satisfaction, respectively. Two of the three responses in the other category indicated their concern for the environment.

Question 3

"If you selected no, what are some specific concerns you see in implementing AI tools for reducing food waste in your establishment?"

Understanding negative perceptions is crucial for identifying targeted solutions. Participants who chose 'No' for question 1 were asked about specific concerns they have about implementing AI tools for reducing FW in their establishment. Table 15 below captured the responses received for the negative perception.

Table 15

Reasons for Negative Perception

Concern	Rank		
	1	2	3
Limited access to technology	1	1	4
Data availability and quality of data	1	2	4
Government regulations and data privacy laws	1	2	2
Lack of awareness of AI solutions	1	7	0
Skill gap, training needs and resistance to change	2	0	5
Cost of implementation	7	2	0
Other	0	0	0

Note. The ranking system is ranked from 1 to 3, with rank 1 being the highest and rank 3 being the lowest.

It appears that the negative perception of AI applications for FW reduction is driven by the perceived high cost of such applications. In addition, a lack of awareness of AI solutions also appears to be a concern influencing the negative perception of the participants. On the other hand, skill gaps, training needs and resistance to change seem to be the least concern.

Question 4

"If you are unsure, what information or evidence would help you feel more confident about AI's potential for reducing food waste in the Hospitality Industry?"

Skeptical responses reveal the specific concerns and reservations stakeholders have about AI. Further, by analysing these responses misconceptions about AI can be addressed. Table 16 below highlights the responses to the above question.

Table 16

Sceptical Responses

Category	N	Rank
Examples of successful AI implementations in similar businesses	27	2
Data security and privacy guarantees of AI systems	16	4
Clear cost-benefit analysis	31	1
Information on user-friendly and affordable AI solutions	26	3
Other	7	5

Participants are most interested in understanding the financial implications of AI adoption. They want to see evidence that the potential cost savings from reduced FW outweigh the cost of implementing and maintaining AI solutions. Seeing concrete examples of how AI has been used effectively in similar hospitality businesses, (ranked at number 2) would address skepticism and build trust in its potential. Concerns about data security and privacy were highlighted, particularly the importance of transparency about how AI systems handle sensitive information within the hospitality industry. It appears that the participants were looking for AI solutions that are not only affordable but also user-friendly for implementation within their specific hospitality operations.

Section 6 – Intentions in Implementing Artificial Intelligent Tools to Reduce Food Waste

This section explores the future intentions of participants in adopting AI solutions and the challenges associated with this decision. Analysis of the intention to implement AI provides valuable insights into the industry's readiness for this technology. By understanding these intentions, stakeholders can develop more effective strategies for promoting AI adoption. This section comprises four questions assessing the overall interest in AI, factors influencing AI adoption, preferred AI tools and the reasons for non-implementation of AI in the short run.

Question 1

"How interested are you in implementing AI tools to reduce food waste in your hospitality business?"

Figure 12 displays participants' interest in implementing AI tools in their organisations, rated on a scale of 0 (no interest at all) to 10.

Figure 12

Overall Interest in the Implementation of Artificial Intelligence

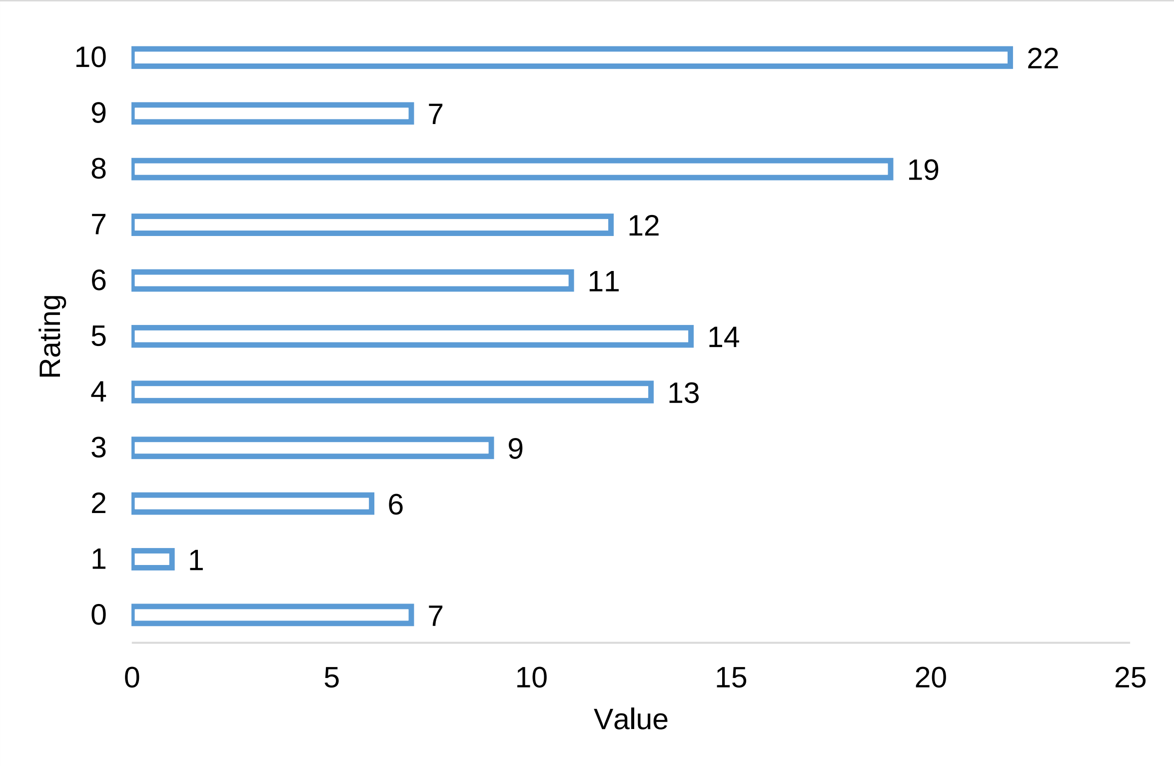


Figure 12 represents the participants' overall interest in implementing AI to reduce FW. Three groups emerged in the analysis; detractor (scores 0 to 6), passive (scores 7 and 8), and promoter (scores 9 and 10). The graph shows that more than half of the participants are either "very interested" or "somewhat interested" in utilising AI to reduce FW. The percentage of "very interested" participants is slightly higher than those who are "somewhat interested". On the other hand, about 22% of the participants have no interest in implementing AI to reduce FW. This could be due to various reasons, such as lack of knowledge, skepticism or belief that traditional methods are more effective.

Overall, the graph indicates that there is a significant level of interest among the participants in utilising AI to reduce FW. This suggests that there is potential for AI-powered solutions to be successful in addressing the issue of FW, provided that such solutions are developed in a way that is accessible, affordable, and easy to use.

Question 2

"What factors would influence your decision to implement AI tools for food waste reduction?"

Table 17 below captures the top three reasons influencing participants' intentions of implementing AI for FW reduction.

Table 17

Factors Influencing Artificial Intelligence Implementation

Area	Rank		
	1	2	3
Proven effectiveness in reducing food waste	24	30	28
Cost-effectiveness	45	33	10
Ease of implementation	10	26	28
Compatibility with existing systems	17	20	21
Others	2	3	5

Note. The ranking system is ranked from 1 to 3, with rank 1 being the highest and rank 3 being the lowest.

The table presents a ranking of factors influencing the decision to implement AI tools for FW reduction, based on their perceived importance. Proven effectiveness in reducing FW received the most balanced distribution of rankings. Cost-effectiveness is arguably the most decisive factor for implementation, with the majority ranking it as the highest priority. It indicates that the financial aspect of AI tools is a critical consideration for decision-makers. Ease of Implementation has a diverse distribution, with a notable number of respondents considering it of the lowest importance. This implies that while ease of implementation is a factor, it is not as critical as cost-effectiveness or proven effectiveness. The rankings are quite evenly spread across all three levels of importance concerning compatibility with existing systems, suggesting that compatibility is a moderate concern for most respondents. Among the reasons in the other category are data privacy and security measures, human errors and that AI is 'easy to implement but hard to train'.

Analysed below are the top three reasons based on the three groups – detractor, passive and promoter.

Table 18

Participant Concerns Based on Category of Responses

Category	Rank		
	1	2	3
Detractor	Cost-effectiveness	Proven effectiveness	Ease of implementation
Passive	Proven effectiveness	Cost-effectiveness	Proven effectiveness
Promoter	Cost-effectiveness	Cost-effectiveness	Proven effectiveness

The above table shows the top three concerns for participants who fall into the categories of Detractor, Passive, and Promoter. For Detractors, cost-effectiveness is their top concern, followed by proven effectiveness and ease of implementation. This indicates that they are primarily concerned with the cost of AI applications, as well as the evidence that it will work, and the ease of implementing it. For Passives, proven effectiveness is their top concern, followed by cost-effectiveness and proven effectiveness (again). This suggests that they are more interested in seeing real results from AI applications, but are also conscious of the cost. For Promoters, cost-effectiveness is their top concern, followed by cost-effectiveness and proven effectiveness. This shows that they are most interested in a cost-effective solution, but also value evidence that it works.

In summary, cost-effectiveness stands out as the most influential factor, followed by proven effectiveness. Ease of implementation and compatibility with existing systems are less decisive but still relevant considerations.

Question 3

"What would it be if you were to implement one AI solution tomorrow to address food waste in your establishment?" The question aimed to evaluate participants' readiness to select an option that best suits their needs.

Table 19

Implementation of Artificial Intelligent Tools

AI tool	N
AI-powered recipe scaling to minimise leftover ingredients	26
Smart fridges/pantry systems for predicting spoilage and optimising usage	22
Electronic noses and taste sensors for early detection of food spoilage	11
Image analysis of food waste in plates and bins	18
AI-powered demand forecasting software	21
Other	2
At this time, my organisation does not prioritise implementing AI tools	21

Table 19 shows the different AI tools that the participants would choose if they were tomorrow to implement one AI solution to address FW in their establishment. The most popular option among the participants was AI-powered recipe scaling to minimise leftover ingredients, with 26 respondents choosing it. The second most popular option was smart fridges/pantry systems for predicting spoilage and optimising usage, with 22 respondents choosing it. The third most popular option was AI-powered demand forecasting software, with 21 respondents choosing it. Other options included image analysis of FW in plates and bins (18 responses), electronic noses and taste sensors for early detection of food spoilage (11 responses). One of the respondents indicated that AI tools would be looked at favourably only if the cost of installation and maintenance is lower than the actual cost of FW in the organisation. 21 respondents do not wish to implement AI tools any time soon, the reasons for which are discussed in question 4 below.

Question 4

"If you choose not to implement AI tools shortly, what is the single biggest reason?" The question aimed to understand the main obstacles organisations face in implementing AI-driven applications for FW reduction.

Table 20

Reasons for Non-Implementation

Reasons	N
Limited access to technology infrastructure in my area	3
Lack of well-organised data for AI analysis in my establishment	2
Concerns about the costs of implementation and maintaining AI systems	6
My business operation is too small to justify the investment in AI tools	8
Other	2

My business operation is too small to justify the investment in AI tools is the most common reason, with 8 mentions. This suggests that for many, the perceived return on investment does not align with the scale of their operations. Some of the comments provided by the respondents corroborate this. Concerns about the costs of implementation and maintaining AI systems are next with 6 responses. Cost is a significant barrier, indicating businesses are wary of the financial commitment required for AI integration. Limited access to technology infrastructure in my area has been cited, showing that infrastructural limitations are also a concern, however less important than cost and scale. The lack of well-organised data for AI analysis in my establishment has the second-lowest frequency, with 2 responses. This implies that while data organisation is a challenge, it is not as pressing as other concerns. Other responses included the company's inability to accurately target its customers and the belief that AI is incapable of comprehending real-life scenarios.

Section 7 – Sustainability Goals

This section examines the sustainability goals of organisations and the role of AI in achieving these goals.

Question 1

“In your opinion, what potential benefits do you foresee in implementing AI technologies for food waste reduction in achieving broader sustainability goals in your establishment?” The question aimed to understand the various sustainability goals that may motivate the adoption of AI-powered FW reduction. For instance, organisations aiming to achieve environmental goals may prioritise AI solutions that enhance resource efficiency and decrease their carbon footprint.

Table 21 captured the responses to the above question, ranked in order of importance, with 1 being the highest to 3 being the lowest.

Table 21

Sustainability Goals

Sustainability Goal	Rank		
	1	2	3
Reducing environmental impact through resource conservation	34	27	23
Enhancing community engagement and sustainability initiatives	11	30	12
Improving brand reputation and customer perception	19	18	20
Achieving cost savings and increased profitability	45	20	15
Contributing to broader sustainability goals of the industry	17	18	24
Other	1	0	0
None	4	1	0

Note. The ranking system is ranked from 1 to 3, with rank 1 being the highest and rank 3 being the lowest.

Reducing environmental impact through resource conservation is considered a high priority by most respondents (34), reflecting the environmental consciousness of the businesses. Enhancing community engagement and sustainability initiatives has a balanced distribution across the rankings and has the highest number of responses in the middle category (30). This suggests it is seen as important, but not the top priority. The responses to improving brand reputation and customer perception are evenly distributed, indicating that while important, it's not consistently seen as the most critical sustainability goal. Achieving cost savings and increased profitability received the most responses as the highest priority (45). This emphasises the industry's focus on the economic benefits of sustainability. Contributing to broader sustainability goals of the hospitality industry was ranked as the lowest priority (24). This may indicate a focus on immediate, tangible benefits over broader, long-term goals. A few respondents (4) do not prioritise any of the listed sustainability goals, which could reflect a lack of awareness or a different focus within their operations.

In summary, while environmental conservation and cost savings are seen as the most important sustainability goals, community engagement, brand reputation, and broader industry goals are recognised. However, the emphasis varies, suggesting diverse priorities and strategies within the hospitality sector.

Correlation analysis

This section investigates the relationships between several variables to gather more insights into the role of AI in FW reduction and the factors shaping the relationship. Table 19 presents the correlation analysis of various categories related to the hospitality industry in New Zealand. The categories include; age, gender, occupation, experience, establishment type, location, employees' size, years in operation, FW, AFW, familiarity with AI, perception of AI, and implementation of AI.

The correlation coefficient, represented by ρ and r, measures the strength of linear association between two variables, ranging from +1 to -1, indicating the degree of association between two sets of measurements. The study adopted Spearman's correlation technique to establish relationships between the variables.

Table 22

Correlation Analysis

Category	*Age*	*Gender*	*Occupation*	*Experience*	*Establishment type*	*Location*	*Size of establishment*	*Years in operation*	*Food waste percent*	*Avoidable food waste*	*Familiarity overall*	*Perception*	*Implementation*
Age	1.00												
Gender	0.10	1.00											
Occupation	-0.30	0.08	1.00										
Experience	0.50	-0.06	-0.63	1.00									
Establishment type	0.19	0.01	0.07	0.10	1.00								
Location	0.24	0.34	-0.13	0.25	0.06	1.00							
Size of Establishment	0.06	0.03	0.21	-0.01	0.14	0.06	1.00						
Years in operation	0.29	-0.02	-0.10	0.28	0.18	0.08	0.48	1.00					
Food waste percent	0.02	-0.02	0.20	-0.11	0.17	-0.05	0.20	0.10	1.00				
Avoidable food waste	0.10	0.13	0.23	-0.14	0.13	-0.07	0.05	-0.17	0.25	1.00			
Familiarity overall	-0.23	-0.09	0.05	-0.10	-0.07	-0.34	-0.25	-0.27	0.09	-0.07	1.00		
Perception	-0.17	-0.15	-0.10	0.09	-0.03	-0.12	-0.28	-0.09	-0.16	-0.20	0.26	1.00	
Implementation	0.11	-0.01	-0.05	-0.06	0.07	0.11	0.26	0.24	0.15	0.02	-0.14	-0.35	1.00

Demographics Shaping Knowledge and Perceptions

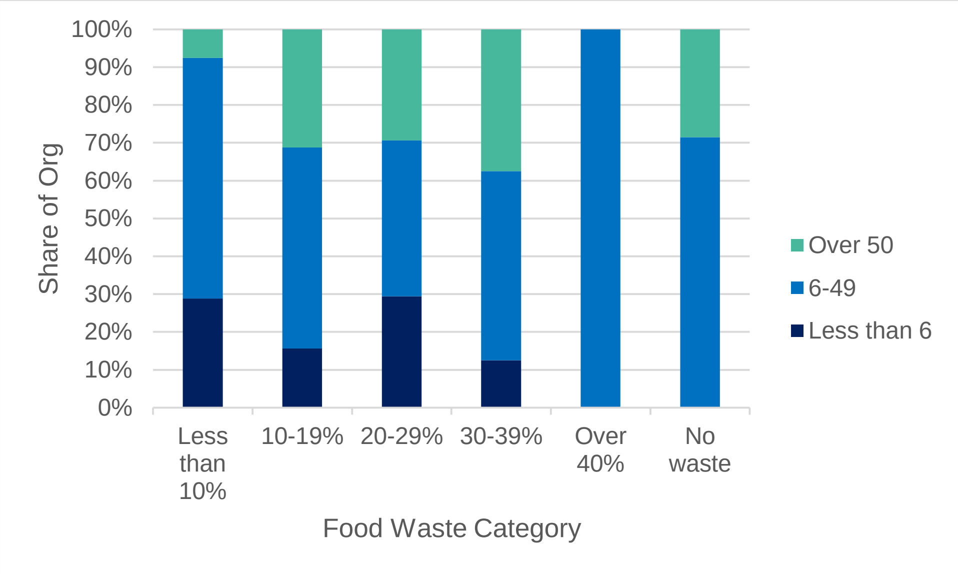
Age shows an inverse relationship with knowledge of AI (-0.23) and perception of AI (-0.17). Only 30% of the participants showed awareness of AI technologies and the data suggests that overall there is moderate familiarity with AI technology among the participants. The negative relationship between age and familiarity with AI applications may be due to a variety of factors. One potential explanation is that younger individuals may have grown up with greater exposure to technology and are therefore more comfortable with new technologies such as AI. Additionally, older individuals may be less likely to seek out information about new technologies or to have access to the same resources as younger individuals. In the study, the greatest awareness was seen in the 35-44 age group (40% of overall familiarity). As one's career progresses, one may gain more exposure to various technologies. The same reasons may hold for the relationship with the perception of AI.

Food Waste and Avoidable Food Waste and their Relationships with Type and Size of the Organisations

Food waste and AFW are positively correlated with the establishment type ($r = 0.10$ and $r = 0.25$, respectively). This could be because certain establishment types may generate more FW and AFW than others, for instance, hotels have a higher FW compared to cafés/coffee shops (Figures 8 and 9). Food waste shows a positive correlation ($r = 0.20$) with the size of the organisation. Figure 13, below, captured FW by the size of the establishment, represented in terms of the number of employees.

Figure 13

Food Waste by Employees (Size of Organisation)



Based on the above figure, it is clear that larger organisations tend to have higher levels of FW compared to smaller organisations. This trend is evident across the FW categories exceeding 10%. Complex menus and portion control challenges, customer expectations, buffet-style services and lack of awareness/training among the staff lead to higher waste in larger organisations (Table 9- Causes of FW). Approximately 5% of the overall responses fall into the 'no waste' category.

Avoidable food waste has an insignificant (r = 0.05) relationship with the size of the organisation. Besides, approximately one-third of the organisations are uncertain or unable to estimate their AFW (Figure 9). Of these, almost 30% are hotels and 20% each are fine dining and casual dining restaurants. Complexities of food service operations in hotels in particular, for instance, large buffets to a la carte and in-room dining may make tracking AFW challenging.

Relationships between Knowledge, Perception and Implementation of Artificial Intelligence-Driven Technologies and Variables Shaping these Relationships

An understanding of a participant's level of AI knowledge can shed light on why they might be interested or hesitant to adopt AI solutions for FW reduction. The inverse relationship of -0.14 indicates that the study found that even though some participants had an understanding of AI-driven applications, this knowledge did not necessarily translate into an interest in implementing AI in their organisations. Cost-effectiveness was the topmost factor that influenced the decision to implement AI tools for FW reduction among the detractor group. This group was not convinced that the benefits of AI outweighed the costs. However, the passive group was more inclined towards the proven effectiveness of AI tools, while the promoter group favoured cost-effectiveness as their primary reason for implementing AI tools. What is intriguing is that one-fifth of the participants who had not heard of or experienced any AI technologies designed for FW reduction were promoters of implementing AI tools.

The study examined the relationship between perceptions of AI effectiveness and the participant's role within their organisation. The analysis revealed a negative correlation (r = -0.10) between the two variables. The negative correlation suggests that decision-makers may perceive AI positively due to its potential cost savings or efficiency gains, while operational staff might be concerned about the potential job displacement due to AI automation. Mrowinski et al.'s 2020 study on AI and automation's impact on employment revealed that these technologies significantly disrupt employment relationships and decrease the number of workers performing specific tasks. Interestingly, approximately 30% of the owners/managers believed AI technologies could significantly reduce FW, while the same was 40% for those with a negative perception. Decision-makers who were unsure accounted for about 43%.

Organisation size versus perceptions of AI is an inverse relationship (r = -0.28). This relationship investigates correlations between the size of the organisation in the participant's perceptions of AI's potential benefits and limitations. The inverse relationship may result from the complexities of operations in larger organisations. Their diverse food service operations make it difficult to standardise AI solutions or perhaps they feel that the existing solutions are adequate. Smaller organisations, on the other hand, have simpler operations that offer agility and perhaps have a more open view or excitement about AI. Conversely, larger organisations might be more aware of AI leading to a cautious approach. It should be noted that 37% of the participants were unsure about the potential of AI in reducing FW, of which 55% were SMEs and 35% were micro organisations. The revised correlation was still inverse (r = -0.11), however, was weaker.

Organisation size and the interest in implementing AI is yet another important relationship which shows a positive (r = 0.26) relationship. This analyses the relationship between the size of the hospitality business (SME vs. large enterprise) and the level of interest in implementing AI solutions. SMEs might be more hesitant due to budget constraints or a lack of technical expertise, while larger enterprises might have the resources to invest in and integrate AI solutions more readily. Larger organisations tend to generate more data, which can be a valuable asset for training and optimising AI models for FW reduction. They might see this as an advantage compared to smaller businesses.

Interestingly, the relationship between perception and interest in implementation is negative (r = -0.35). Participants who perceive AI as less effective for FW reduction might be less interested in implementing it, even if they have the resources (larger organisations). If concerns about data security, cost-benefit analysis, or user-friendliness (as identified earlier) are not addressed, organisations might hesitate to implement AI despite some initial interest.

Larger organisations might be interested in exploring AI (positive relationship with size and interest) due to potential cost savings and data advantages. However, their complex operations, awareness of implementation challenges, and a more critical approach due to the AI hype might lead to a cautious perception of its effectiveness (inverse relationship between perception and size). This cautious perception (inverse relationship between perception and implementation) can translate into a wait-and-see approach or a hesitation to fully implement AI solutions until concerns are addressed and the perceived effectiveness improves.

Thematic Analysis

Thematic analysis is a crucial aspect of qualitative research, identifying patterns or themes within data. It is a flexible method that helps researchers understand, describe, and interpret experiences and perceptions. It is not tied to a specific epistemological or theoretical perspective but is essential for conducting various types of analyses. A good thematic analysis aims to identify important or interesting patterns in the data and use these themes to address research or issues (Maguire & Delahunt, 2017).

The thematic analysis in this study explores participants' views on the potential of AI for reducing FW in the hospitality industry. Five main themes emerged from the data; the potential benefits of AI, challenges and concerns, past experiences, the importance of awareness and education, and environmental consciousness. The following section analyses the responses in detail.

Potential Benefits of Artificial Intelligence

Several participants expressed optimism about AI's potential to benefit the hospitality industry as follows.

"I don't have much idea about AI for food waste management on a small scale but it will work for the big industry"

"Believe AI is the way to go"

"Have not had a chance to work with it but have seen it being done in other countries. Very interested in looking into it"

"Based on the development of AI, I believe it will undoubtedly be beneficial for the hospitality industry in the future, particularly in reducing food wastage through this technology"

Some of the benefits highlighted by the participants are as follows.

Predictive analytics: Identify waste areas and optimise resource allocation by analysing large datasets, AI can pinpoint areas where FW occurs and suggest strategies for improvement.

"Large databases on food production, distribution, and consumption are being analysed by AI to identify possible waste areas and enhance resource allocation and planning."

"AI should be linked to menus and portion size which can result in price modifications and reduced portion size. This will benefit the customer as well knowing that customer will only pay for what can be consumed rather than pay extra and waste food"

Forecasting: AI can analyse historical data and predict customer demand, allowing for more accurate food preparation and waste reduction.

"We can get details of how many meals guests had"

Streamline processes: AI can streamline ordering and ensure food quality, minimising waste throughout the process.

"AI can be used for supply chain optimisation, quality control, demand forecasting, food rescue and redistribution, smart packaging and labelling, consumer engagement, waste tracking and analytics etc."

Challenges and Concerns

While some participants see promise in AI, others raise concerns, such as the following:

Cost-effectiveness: The cost of implementing and maintaining AI solutions is a significant barrier, particularly for smaller businesses.

"Cost of implementation and ongoing costs are major roadblocks in this region. The availability of cost-effective solutions needs to be a priority in NZ"

"If it is going to be expensive to implement compared with the actual waste cost as most of the waste comes from used plates by customers which cannot be resold but only compost"

"Consider the payback period"

Limited effectiveness: Some participants expressed skepticism about AI's ability to fully address FW, highlighting the role of unpredictable customer behaviour.

"AI isn't that helpful as it depends on the customers as well"

"AI is programmed and can make mistakes"

"AI is not very helpful in fine dining as food waste will occur due to customer's wrong choice of the menu"

"Cannot be a fully AI environment, AI doesn't reflect on experience and expectation! Hence AI should be used smartly"

"Cannot incorporate industry awareness and seasonal patterns"

"AI is a software which only works on a few areas effectively, AI can be used to get orders. XXX is going to use AI in New Zealand for order-taking. AI cannot reduce food wastage by 100%. The main thing will be the demand forecast and work accordingly. The just-in-time basis is the ideal method to reduce food waste whereby preparation can be done based on historical demand on walking customers and bookings"

Negative impact on staff: There is a concern that AI might increase the workload for kitchen staff or lead to job displacement.

"An AI System needs to avoid adding workload to kitchen personnel"

Past Experiences

A few participants shared past experiences with AI FW reduction systems, with mixed results. Some found them underwhelming, highlighting the need for improvement in future iterations.

"Years ago we bought an AI system...Not super impressed by it"

Importance of Awareness and Education

Several participants emphasised the importance of raising awareness about AI and educating stakeholders on its potential benefits and limitations. This includes creating training programs and workshops to foster understanding and encourage adoption.

"Creating a wider awareness through media, training programmes or government-sponsored workshops of the pros and cons of AI is important"

Environmental Consciousness

Many participants expressed their concern for the environment and that FW needs to be minimised.

"There are a lot of people around the world without a single meal per day Save the planet"

"Even though it is not economically beneficial it is ecologically beneficial"

Overall, the data suggests cautious optimism about AI's potential for reducing FW in the hospitality industry. While participants acknowledge its potential benefits, concerns regarding cost, effectiveness, and impact on staff need to be addressed. Additionally, raising awareness and educating stakeholders will be crucial for successful implementation.

Summary

These findings suggest a diverse range of participants in terms of gender, age, occupation, and experience, with certain categories being more prevalent than others. This diversity can provide a broad perspective on the subject matter of the study. Overall, the analysis revealed that there is a growing interest in the use of AI for FW reduction in the hospitality industry in New Zealand. Many respondents highlighted the potential benefits of using AI, such as reducing costs, improving efficiency, and enhancing sustainability. However, there were also concerns about the cost and feasibility of implementing AI solutions, hence, there is 'a wait-and-see' approach to implementing AI solutions for FW reduction.

Chapter 5 - Discussion

This chapter explores the research questions in light of the literature and attempts to evaluate the potential use of AI technology in reducing FW in the hospitality industry. It also examines stakeholders' knowledge, perceptions, and attitudes towards AI integration and its effectiveness. Also discussed is how AI technology aligns with sustainability efforts in the sector. The chapter provides a comprehensive view of AI's potential in driving FW reduction and offers a platform for scholarly interpretation and judgment of the findings.

Food Waste, its Causes and the Role of Artificial Intelligence

The survey showed that 51% of respondents believe they have a low percentage of FW, with 53% mentioning AFW below 10%, and 25% unsure about their AFW levels. However, caution must be exercised when interpreting self-reported data. Studies have shown that businesses tend to report less FW overall than audits reveal. For instance, in a study conducted by Jones (2017) of FW in restaurants and cafes in New Zealand, self-reported AFW levels were significantly lower than the actual levels. According to Chisnall (2017), AFW stands at over 60% in the cafes and restaurants in New Zealand, with the majority self-reporting their AFW as being less than 20%.

One of the key drawbacks of FW mitigation is the lack of understanding of measuring FW or the non-availability of standard criteria for measurement (Chisnall, 2017; Filimonau & De Coteau, 2019). Efforts to educate on FW reduction could target the 'unsure' group to potentially make a significant impact. According to Filimonau and De Coteau (2019), employees who are educated about the impact of FW are more likely to engage in minimising it and share this information with customers. However, employees can also hinder this process due to a lack of training and resources which can in turn delay or prevent employees from adhering to mitigation practices (Filimonau & De Coteau, 2019).

The study found that there is a positive correlation between FW and the type of establishment/sub-sector. This means that certain types, such as hotels (as seen in Figure 8) displayed a broad spread of FW across all categories, with a higher tendency towards the

10% to 29% waste range compared to cafes or coffee shops which were skewed towards the less than 10% waste category. Karakas's 2021 study on FW management in luxury hotels in Budapest highlighted that waste generation is higher in the kitchen, breakfast open-buffet, and staff canteen. The study also found that disposing of food is often cheaper than reusing or donating it. In luxury hotels, the primary challenge is to strike a balance between providing a 5-star experience and minimising FW.

Fine dining restaurants were found to have significant FW in the 10%-19% and 20%-29% categories, with 6% exceeding 40% of waste (as seen in Figure 8). The study by McAdams et al. (2019) revealed that meal preparation and cooking contribute to 74% of FW in the kitchens of fine dining restaurants. Filimonau et al. (2019) attribute this to the stricter standards for visual appearance that fine dining restaurants apply to their dishes. As a result, chefs tend to reject plates that do not meet their aesthetic requirements, leading to FW in the kitchen (Charlebois et al., 2015). To prevent FW, resourceful cooking is essential, as noted by Thompson and Haigh (2017). Although chefs understand the manifold negative implications of excessive FW, few engage in FW prevention. Filimonau et al. (2023) identify the lack of skills in resourceful cooking among chefs as the main reason for their disengagement.

A segment which has recorded a significant AFW is the catering services. Catering businesses produce large volumes of waste, and reducing it can be complicated. The sheer volume of food they need to prepare means they may have less flexibility when it comes to personal preferences (Great Western Recycling, 2022). With better practices or technology, they feel that over 60% of FW could be avoided. Interestingly, 5% of the participants reported no waste in their establishments. According to Artash (2022), many successful zero-waste restaurants, for instance, zero-waste restaurants in India, such as New Krishna Bhavan and Eat Raaja, manage organic waste responsibly and recycle items.

The study revealed that inaccurate demand forecasting is a high cause of FW, while portion control and plate waste are seen as low and high causes. Inefficient inventory management and supply chain challenges are viewed by a majority as a low cause of FW. Lack of FW awareness/training is consistently identified as a cause of FW across the categories studied. These differences could reflect operational differences and customers' social practices related to food consumption (Papargyropoulou et al., 2019). Understanding these factors contributing to FW is crucial for developing effective reduction strategies.

Looking at FW within the sectors, the results show that inaccurate demand forecasting is a significant cause of FW, particularly, in catering services. Wu et al. (2021) iterate that the catering sector faces significant challenges due to uncertainty about customer demands and inaccurate forecasting, leading to excessive ingredient purchases and FW. AI-driven applications have been proposed to address these issues, such as the Ingredient Planner, an AI-powered mobile application that helps customers and caterers find required ingredients (Arvindaraj et al., 2023). Other studies have focused on FW management in Portuguese catering units by creating an intuitive dashboard (Amaro et al., 2021), using ML approaches to predict future guest attendance and RF approaches to avoid over-catering (Malefors et al., 2019). A demand forecasting system using a stacking technique predicts customer numbers, sales for specific dishes, and raw material consumption, potentially reducing FW (Harshini et al., 2021). Santos et al. (2021) tested three ML algorithms to estimate food requirements, finding that ML algorithms outperformed human prediction in certain instances, helping to reduce FW and save resources in college restaurants. Studies by Faezirad et al. (2021) and Aci and Yergok (2023) show that incorporating uncertainty into demand prediction models can lead to effective FW reduction. However, Li et al. (2019) suggest a combination of ML algorithms and human expertise for more accurate demand predictions. Rodrigues et al. (2024) proposed four machine learning models to improve food forecasting accuracy in catering services reducing wasted meals and unmet demand by 14%-52% and 3%-16%, respectively.

Fine dining restaurants, casual dining restaurants and pubs cited portion control and plate waste as the leading cause of FW. Dhir et al. (2020) agree that plate waste is a concern in both settings, in general, casual dining restaurants have greater plate waste volume than fine dining restaurants (Dhir et al., 2020). According to Hawkins (2019), a significant 34% of FW is due to plate waste in UK pubs. Artificial intelligence-driven sensors and data analytics have been used to reduce FW arising as a result of plate waste in the hospitality sector. Pu et al. (2022) developed a method to detect dish waste in restaurants using image processing and DL technology, improving label recognition accuracy. Sarapisto et al. (2022) used ceiling-mounted cameras and CV to estimate food intake accurately, reducing waste and improving nutritional intake. Farinella et al. (2020) used CNN-based image processing to reduce FW in a dining hall. Wen et al. (2018) and Hong et al. (2014) developed IoT-based waste management systems, achieving 33% average waste reductions. Koivunen et al. (2020) developed an intelligent self-serve lunch line equipped with sensors to collect data on customers' eating habits, preferences, and bio-waste generation. Cheng and Leong (2023) developed an AI-powered plate waste tracker, enabling chefs to optimise menus and reduce waste. Principato et al. (2023) used advanced ML algorithms to analyse waste in a company canteen, identifying key factors associated with waste generation and enabling targeted interventions in kitchen and consumer behaviour. Uğur Genç et al. (2019) developed an intelligent menu design using AI and ML algorithms to create adaptive persuasive technologies, suggesting complementary dishes to reduce waste and encouraging customers to use abundant items.

Concisely, AI-powered technologies have shown promise in reducing FW in the hospitality sector, particularly in forecasting portion control and plate waste reduction. These technologies, including image processing, ML, DL, CV, and IoT-based systems, can accurately detect dish waste, estimate food intake, and provide real-time data on waste generation and customer behaviour. Advanced ML algorithms can also identify waste-related factors for targeted interventions.

Lack of FW awareness and training was the key cause of FW highlighted in hotels and fast food restaurants. Kasavan et al. (2019) and McAdams et al. (2019) identified the skill levels of employees as one of the causes of FW in the hospitality and food service sector. According to Afzal et al. (2022), the hospitality sector is often not tracking FW due to a lack of awareness about cost savings. They argue that raising awareness and providing technical training could increase the adoption of food-tracking practices and reduce FW. According to Rady et al. (2021), staff behaviour plays a crucial role in reducing FW. Encouraging staff to understand the key factors of FW generation and the opportunities to reduce it is essential. Training staff on plating practices and waste reduction programs among other things is crucial in overcoming FW, argue Rady et al. (2021). Dhir et al. (2020) stress that all food service establishments should be made responsible for training their kitchen and serving staff in different FW reduction methods and approaches.

It is equally crucial to educate both staff and customers. In terms of creating awareness among customers, Onyeaka et al., (2023) stress that AI-based apps can educate consumers on meal planning, storage, and home waste reduction through personalised information tips. Zhao and Dai's 2023 study found that FW is significantly influenced by personal characteristics, family background, food conservation promotion, and dining characteristics, using ML models. Christine and Latifah's 2022 study on FW found that raising awareness, improving canteen management, and promoting sustainable consumption behaviours were effective strategies for reducing FW, using the AI methods. Cheng and Leong (2023) proposed an FW reduction approach that includes carbon and nutrition labelling on dishes, allowing guests to understand the environmental and health impacts of their choices. They also offered a custom-built nutrient-tracking website for personalised selections. The study highlights the importance of consumer awareness and behaviour change in reducing FW, particularly customer plate waste.

The study found that inefficient inventory management and storage are less significant factors causing FW than other factors. However, inventory management is crucial for ensuring freshness, monitoring shelf life, preventing spoilage, and tracking inventory levels for restocking. Ufot et al. (2021) developed a Model-View-Controller framework and data visualisation tools for university food pantries to enhance inventory management and minimise waste. van der Walt and Bean (2022) proposed a multi-objective inventory decision-making model for in-flight catering, considering waste minimisation.

The issue of FW in the hospitality sector has been a growing concern, with numerous studies indicating that it is a significant contributor to economic, environmental and social degradation. To tackle this problem, there has been a growing interest in the potential of AI tools to reduce FW across the industry. Studies have shown that AI tools, such as predictive analytics, can help food service providers better manage their inventory, forecast demand, and reduce overproduction. By using real-time data to predict demand, these tools can help chefs and managers make informed decisions about how much food to prepare, thus, reducing the likelihood of excess food being thrown away. Moreover, AI-powered apps and platforms can help restaurants and hotels to better manage their FW by tracking how much food is being thrown away, where it is being wasted, and the reasons behind this. This information can then be used to develop targeted training programs and initiatives to address these factors, reducing the amount of FW generated by the hospitality industry.

Artificial intelligence-driven tools have demonstrated significant potential in reducing FW in the hospitality sector, potentially playing a pivotal role in combating FW in New Zealand's hospitality industry.

Knowledge of Artificial Intelligence Driven Tools for Food Waste Reduction in Hospitality

Despite the rising concerns about the impact of the hospitality industry FW on the sustainability pillars, the industry is still lagging in adopting AI technologies to reduce FW. According to the survey, only 30% of industry professionals are familiar with AI, and nearly 70% remain unaware of its potential applications in minimising FW, highlighting a significant gap in the awareness of AI technologies within the hospitality industry, concerning FW reduction. The outcome can be viewed from industry-specific reasons and environmental factors. Firstly, the focus on traditional practices, the size and scale of businesses (97% of all businesses in New Zealand are SMEs), and a lack of widespread existing AI applications in the sector could be some of the causes creating this gap. Many hotel General Managers view technology as 'a nice-to-have' rather than 'a game-changer' for their businesses (DKube Inc.,2023). On the other hand, many hoteliers still need to understand how AI can benefit their businesses, making them hesitant to invest in AI (DKube Inc. 2023). Moreover, the quality of data in hotels is often poor, collected from various sources and not standardised, making it challenging to integrate and analyse (Johansson, 2023).

On the other hand, country-wide, 49% of New Zealand organisations are yet to adopt any form of AI, according to a survey carried out by Datacom on 200 top executives in New Zealand organisations with 100+ employees. This may not be representative of the economy as a whole as, according to StatsNZ (2020), only 2690 big businesses in New Zealand employ more than 100 staff. The Ipsos Global Advisor survey revealed that only 35% of New Zealanders are familiar with AI-powered products and services. New Zealanders are more sceptical of AI than the rest of the world (Ipsos, 2023), and IT departments in Australia and New Zealand are the lowest adopters of AI and ML technologies, with only 27% having done so, falling short of the global average of 44% (Zulhusni, 2022).

Of the 30% of respondents who have an understanding of AI in hospitality for FW reduction, the data suggests moderate familiarity overall with AI technology. Additionally, there is a varying degree of familiarity with the different applications of AI in reducing FW. Based on the responses, it appears that the participants are more familiar with intelligent kitchen management systems and forecasting demand using ML. At the same time, they are less familiar with sensors and devices that identify food spoilage and smart bins. This could be an area needing deeper understanding as survey results show that portion control and plate waste are key causes of FW in the hospitality industry in New Zealand.

AI-driven applications, such as Winnow technology, automate the recognition and measurement of FW, recording and weighing unconsumed products by categories such as expired stock, leftover buffets, cooking errors, and plate returns. It provides detailed information on waste by ingredient or recipe, enabling kitchen teams to implement action plans to reduce wasteful foodstuffs. Therefore, to increase adoption of AI technologies for FW reduction it is necessary to educate industry professionals on their potential benefits.

Of the 70% who do not use AI for FW or are unaware of AI tools used for FW reduction, the most common method of the majority for FW reduction is educating staff and customers (28%), altering menu choices (25%), FW tracking or FW audits (17%), inventory management software (13%), and the least cited, composting/donating (12%). According to Chisnall (2017), participants reported difficulties in donating left-overs or excess food stock to food rescue charities such as Food Share and Kiwi Harvest. This was due to a lack of adequate/right type of food, a lack of a local food rescue provider, local council regulations, and liability concerns about food poisoning and unsafe handling. Jones (2017) identified common policies and procedures for businesses to monitor and reduce FW, including; staff training, portion control, flexibility in food ordering, forecasting, stock rotation, doggy bags, and menu changes based on current stock.

The industry could make use of the existing AI applications in food donations. For instance, Varghese et al. (2021) developed a mobile app incorporating AI principles, particularly Human-Computer Interaction, to facilitate food donation and provide relevant information for suppliers and consumers. Zhou et al. (2021) developed an AI-based software application that allows volunteers to pick up food from food pantries and deliver it to homes. The application significantly decreased waste, benefiting restaurants by reducing waste and carbon emissions. Furthermore, the industry could adopt other AI-driven FW reduction solutions, such as smart bins, sensors, and devices that identify food spoilage. These can significantly reduce FW.

Briefly, the hospitality industry in New Zealand can significantly reduce FW by adopting AI technologies. However, the industry needs to increase awareness of the potential benefits of AI for FW reduction. Additionally, the industry needs to leverage the existing AI applications in food donations, and at the same time, focus on adopting other AI-driven FW reduction solutions, such as smart bins, sensors, and devices that identify food spoilage.

To address these issues, providing more opportunities for individuals to learn about and interact with AI technology may be helpful. This could include providing access to educational resources and training programs and increasing the availability of AI-powered devices and systems in various settings. Additionally, raising awareness of the benefits of reducing FW through AI technology could help to increase interest and engagement in the subject among individuals and organisations as stated by one of the participants "Creating a wider awareness through media, training programmes or government-sponsored workshops of the pros and cons of AI is important." Overall, the promotion of AI awareness and education in New Zealand on a national level could help to create a more sustainable future, both within the hospitality industry and beyond.

Perception towards Artificial Intelligence for Food Waste reduction in the Hospitality Sector of New Zealand

The survey revealed a majority of respondents have a positive perception of AI's potential to decrease FW. The majority believe that AI tools would bring cost savings and improved revenue, while also improving operational efficiency, data-driven decision-making, real-time monitoring, and customer satisfaction. However, a significant portion of respondents are sceptical, with over one-third being unconvinced. The negative perception of AI applications for FW reduction is attributed to the perceived high cost and lack of awareness of AI solutions. The least concerns are; skill gaps, training needs, and resistance to change. Over two-thirds of those unsure cited a clear cost-benefit analysis as a solution. Information about successful AI implementations and user-friendliness of such systems was also cited as useful.

New Zealanders, on the whole, exhibit a complex relationship with AI. While a significant portion acknowledge its potential to revolutionise daily lives, a national undercurrent of nervousness and scepticism persists, as per the Ipsos Global Views on AI

2023 Survey. This national hesitancy towards AI, evidenced by lower trust in data privacy and higher anxiety, compared to global averages, likely contributes to the varied perceptions of AI for FW reduction within the hospitality industry. Understanding public perception and AI requirements is crucial for responsible research and innovation, ensuring future AI systems align with individual and societal needs, and promoting responsible development and governance (Brauner et al., 2023). Societal perceptions of AI's impact are linked to trustworthiness, associated risks, and usage acceptance. Those discerning AI's threats often view its prospective outcomes pessimistically, while proponents acknowledge its transformative potential, reflecting trust and AI's uniqueness. (Gerlich, 2023). Artificial intelligence remains a "black box" for many, with no assessment of opportunities or risks, potentially leading to biased public perception. Promoting AI literacy can help facilitate informed decision-making (Brauner et al., 2023). Understanding these broader national views on AI is crucial for dissecting the specific concerns and opportunities surrounding AI adoption in New Zealand's hospitality sector.

The survey identifies perceived high costs as a major deterrent for hospitality businesses. New Zealand's SMEs dominate the hospitality sector, and upfront costs for AI solutions can be a barrier to entry. Understanding individual perspectives is crucial for the adoption and diffusion of AI and ML technologies, as perceived barriers can significantly delay their adoption or increase acceptance (Young et al., 2021)

Low familiarity with AI solutions translates to scepticism about their effectiveness. Many hospitality businesses might not be aware of the diverse and potentially affordable AI solutions. In addition, availability of financing is an important factor: Duppati et al., (2021) state that insufficient financial support is a significant obstacle that hinders the growth of SMEs in New Zealand. Further, according to Wang (2024), the hotel industry in New Zealand is hesitant to adopt AI due to the lack of clear legislation, causing a cautious approach among managers. Despite an interest in integrating AI into operational aspects, concerns about legal implications, data privacy, and potential impacts on customer service quality are weighing on enthusiasm for its integration.

Briefly, the survey revealed that while there is a positive perception towards the potential of AI in reducing FW in the hospitality sector of New Zealand, there is also a significant amount of scepticism. The negative perception is primarily attributed to the perceived high cost and lack of awareness of AI solutions. It is essential to promote AI literacy to facilitate informed decision-making, and financing availability is also an important factor to consider. Adopting AI and ML technologies in New Zealand's hospitality sector could be influenced by acceptance or delayed by perceived barriers.

Artificial Intelligence Implementation in New Zealand

The study reveals that over half of the participants are interested in using AI to reduce FW, with a significant percentage being 'very interested' and 'somewhat interested'. However, 22% have no interest. This is possibly due to a lack of knowledge, scepticism, or a belief in traditional methods. The results suggest that there is potential for AI-powered solutions to be successful in addressing FW, provided they are accessible, affordable, and easy to use. The study found that even though some participants had an understanding of AI-driven applications, this knowledge did not necessarily translate into an interest in implementing AI in their organisations.

Proven effectiveness in reducing FW received the most balanced distribution of rankings, with cost-effectiveness being the most decisive factor for implementation. Ease of implementation had a diverse distribution, with some respondents considering it of the lowest importance. Compatibility with existing systems was a moderate concern for most respondents. Data privacy and security measures, human errors, and the belief that AI is "easy to implement but hard to train" were also considered.

In summary, cost-effectiveness is the most influential factor, followed by proven effectiveness. Ease of implementation and compatibility with existing systems are less decisive but still relevant considerations. The most common reasons for not justifying AI investment include; small business operations, concerns about the costs of implementing and maintaining AI systems, limited access to technology infrastructure, lack of well-organised data for AI analysis, inability to accurately target customers, and the belief that AI is incapable of comprehending real-life scenarios. Kelly et al. (2022) found that perceived usefulness, performance expectancy, attitudes, and trust, among others, significantly influence the behavioural intention, willingness, and use behaviour of AI across various industries.

Chisnall (2017) found that many participants feel comfortable with their current FW generation and practices, reducing their inclination for further initiatives. This comfort may be linked to their perception of customer behaviour as the main contributor to FW. This opens opportunities to develop effective strategies targeting customer behaviour drivers, potentially embracing the sector as less judgemental and critical of their business operations.

Wrapping up, this study sheds light on a complex relationship between New Zealand's hospitality industry and AI-powered solutions for FW reduction. While some awareness of AI exists, a significant knowledge gap prevails regarding specific applications for FW reduction. This lack of understanding creates a barrier for stakeholders to recognise the potential benefits of AI. On the other hand, a positive perception exists about AI's potential to reduce FW and improve efficiency. However, this optimism is countered by strong scepticism due to perceived high costs and a lack of awareness about specific AI solutions. Stakeholders exhibit a cautious wait-and-see approach. Concerns about effectiveness, compatibility with existing systems, and data privacy lead to hesitation in fully embracing AI solutions. This cautiousness can hinder the actual implementation of AI and limit its potential impact on FW reduction. Knowledge, risk perception, and opportunity assessment significantly predict general AI use intention, with higher knowledge levels positively influencing intention to use AI-based applications (Potinteu et al., 2023).

To sum up, the study highlighted a significant gap in awareness and adoption of AI technologies for FW in the hospitality industry in New Zealand, with only 40% of respondents having encountered AI in their careers. The study identified several reasons for this gap, primarily cost-benefit analysis and a lack of understanding of how AI can benefit businesses. Educating industry professionals on the potential benefits of AI technologies for FW reduction is necessary to increase adoption. Overall, the findings established the research question, highlighting the need for increased awareness and adoption of AI technologies for FW reduction in the hospitality industry

Sustainability Goals and Artificial Intelligence

Businesses have come to realise the importance of measuring profit in tandem with social and environmental responsibility to better understand the true costs and benefits of sustainable practices (Alhaddi, 2015). This holistic approach not only benefits the environment but also contributes to building a more resilient and sustainable food industry.

Emerging AI technologies offer a powerful tool in this fight. By analysing historical data and predicting future trends, AI systems can optimise food preparation, purchasing, and inventory management, significantly reducing waste (Martin-Rios et al., 2023; Onyeaka et al., 2023). This aligns with the hospitality industry's broader sustainability efforts in several key ways. Food waste in landfills decomposes, releasing methane, a potent greenhouse gas that contributes significantly to climate change, as noted by Papagargyropoulou et al. (2019). AI-driven solutions that minimise waste directly translate to reduced greenhouse gas emissions, supporting SDG 13 (Climate Action). Resource conservation is yet another area where AI can play a lead role: Food production consumes vast quantities of water, energy, and land. Minimising waste through AI-powered demand forecasting and optimised purchasing translates to reduced resource consumption (Onyeaka et al., 2023), aligning with SDG 12 (Responsible Consumption and Production) and SDG 6 (Clean Water and Sanitation). Food waste represents a significant financial burden for hospitality businesses. AI-driven solutions that optimise food preparation and purchasing can lead to substantial cost savings, improve financial sustainability (Hotel Technology News, 2023) and align with SDG 8 (Decent Work and Economic Growth). AI-powered data analytics can provide valuable insights into FW patterns and their associated environmental and economic impacts. This transparency facilitates informed decision-making, aligning with the sustainability reporting standards (Snežana Janković & Curovic, 2023) and contributing to SDG 12 (Responsible Consumption and Production). Reducing FW demonstrates a commitment to the well-being of local communities. By minimising resource consumption and contributing to environmental sustainability, the hospitality industry can foster responsible community engagement, aligning with SDG 11 (Sustainable Cities and Communities).

There is a growing interest from consumers towards sustainable organisations. Three-fourths of consumers prioritise sustainability, and (84%) say that a lack of sustainability efforts will alienate them from a brand (Hospitality Technology, 2023). The findings of our study suggest that most respondents prioritise reducing environmental impact through resource conservation, reflecting businesses' environmental consciousness. However, enhancing community engagement and sustainability initiatives is seen as important but not the top priority. Improving brand reputation and customer perception is equally distributed, suggesting it's not consistently seen as the most critical sustainability goal. Achieving cost savings and increased profitability is the highest priority, emphasising the industry's focus on the economic benefits of sustainability. Contributing to broader sustainability goals of the industry is the lowest priority, possibly focusing on immediate benefits over long-term goals. A few respondents do not prioritise any of the listed sustainability goals, suggesting a lack of awareness or different focus within their operations. In summary, environmental conservation and cost savings are seen as the most important sustainability goals, but community engagement, brand reputation, and broader industry goals are also recognised.

Food waste in the New Zealand hospitality industry is a significant environmental, economic, and social challenge. Artificial intelligence has the potential to accelerate sustainable outcomes, but it requires confidence from stakeholders. Despite global leaders seeing AI as a positive force, there is still work to be done to address risks and unintended concerns. Limited knowledge and diverse stakeholder perceptions hinder the industry's ability to identify key factors contributing to FW, recognise AI's benefits, and develop strategies for AI adoption. Addressing these challenges will pave the way for the strategic use of AI and a sustainable future for the industry.

According to Chisnall's 2017 study importance of financial outcomes, environmental outcomes, and personal outcomes in motivating people to reduce FW was assessed. Two-thirds of participants rated financial outcomes as extremely important (20 out of 31), followed by environmental outcomes (74%). Personal outcomes and reducing guilt were considered less important by only 12 participants. This indicates that financial savings and environmental sustainability are crucial factors in motivating people to reduce FW.

To conclude, achieving sustainability in New Zealand's hospitality industry is shaped by many factors and it appears that many short-term and long-term measures need attention from the stakeholders of the industry. The starting point in this journey is to acknowledge the critical role of addressing knowledge gaps and initial perceptions surrounding AI. By equipping stakeholders with information about AI's potential and alleviating concerns about cost and effectiveness, a path towards implementing AI solutions is a possibility. These solutions, such as AI-powered demand forecasting, predictive analytics, and inventory management, directly target FW management. Furthermore, these lead to environmental benefits, such as reduced resource consumption and greenhouse gas emissions. Additionally, economic gains can be achieved through cost savings associated with less waste. Social goals, potentially including food donation programs, can also be addressed.

This process is cyclical. The insights gained from successful AI implementation inform further knowledge management and staff training. This continuous learning and adjustment emphasises the importance of human-AI collaboration. Trained staff working effectively alongside AI systems underlies the significance of this partnership. Human expertise remains crucial in various aspects; from data quality control to interpreting AI outputs and adapting them to specific contexts. Overall, by incorporating these elements, the study paints a more realistic picture of the journey towards a sustainable future for New Zealand's hospitality industry. It highlights the importance of knowledge, ongoing learning, and human-AI collaboration in harnessing the power of AI for FW reduction. This comprehensive approach acknowledges the challenges and opportunities associated with utilising AI for a more sustainable future in the hospitality sector. Hence, the utilisation of AI in FW reduction aligns with and enhances New Zealand's hospitality industry's overall sustainability and contributes to the United Nations' sustainability goals.

Summary

The hospitality industry is facing significant challenges in reducing FW. The adoption of AI technologies can play a crucial role in addressing these challenges. However, the industry is still lagging in adopting AI technologies, and the majority of industry professionals remain unaware of their potential applications in minimising FW. As the hospitality industry continues to evolve, prioritising sustainability and mitigating FW's environmental impact is essential. Artificial intelligence technologies can play a vital role in this regard. Moreover, national and industry-level changes are paramount to embracing and adopting them to pave the way for a more sustainable future.

Chapter 6 – Conclusion and Recommendations

The hospitality industry in New Zealand faces a significant challenge: FW. This issue not only represents a financial burden but also carries an environmental footprint, economic drain, social injustice and an ethical dilemma. This chapter draws conclusions based on the analysis and discussion of the research presented in the previous chapters. We explored an outline for implementing AI solutions, acknowledging the importance of addressing knowledge gaps and initial perceptions, thereby painting a roadmap towards a more sustainable future. This chapter not only explores the potential benefits of AI but also acknowledges the limitations and areas for further research. Ultimately, we aim to provide valuable insights and recommendations for stakeholders within the industry, paving the way for a future where AI empowers New Zealand's hospitality sector to achieve significant FW reduction and contribute to a more sustainable future. The chapter is presented in four sections. The first section contributes to an overall summary and a conclusion followed by the study's limitations, insights for future research and overall recommendations.

Summary and Conclusion

This research explored the potential of AI to enhance sustainability within New Zealand's hospitality industry, specifically focusing on its role in reducing FW. The findings highlighted a critical issue – the hospitality sector generates significant FW, impacting the environment, economy, and society. Existing measurement methods often underestimate the true volume of FW, making it challenging to implement effective reduction strategies. This is a reminder of the need for the industry to adopt new technologies to reduce FW, and AI is one of the most promising solutions. We attempted to understand how AI can effectively contribute to reducing FW within the hospitality industry. It was found that AI can play a pivotal role in reducing FW in the hospitality industry in several ways, including forecasting demand, optimising inventory management, monitoring food spoilage, and reducing overproduction. For instance, AI-powered kitchen management systems can help chefs optimise their ingredient usage and reduce FW by predicting demand and adjusting production accordingly. Similarly, smart sensors and devices can detect when food is about to spoil and alert staff to take action, reducing the amount of FW. Consequently, we find that AI could be a game changer in the hospitality industry in its march towards achieving SDGs by reducing FW. That said, some organisations believe that their AI applications are unproductive due to the increased workload on kitchen staff, emphasising the need for stakeholders to consider human interactions when implementing AI tools. According to Kelly et al. (2023), in some cultural scenarios, it appears that the need for human contact cannot be replicated or replaced by AI.

We further explored the relationship between New Zealand's hospitality industry and AI-powered solutions for FW reduction. This was done by attempting to understand hospitality industry stakeholders' knowledge, perceptions and attitudes towards integrating AI for FW reduction. We found that while some awareness exists, there is a significant knowledge gap regarding specific applications for FW reduction. This lack of understanding creates a barrier for stakeholders to recognise the potential benefits of AI. A positive perception exists about AI's potential to reduce FW and improve efficiency, however, this optimism is countered by strong scepticism due to perceived high costs and a lack of awareness about AI solutions. Stakeholders exhibit a cautious 'wait-and-see' approach. They are hesitant to fully embrace AI solutions due to concerns about cost-effectiveness, proven effectiveness of AI applications, compatibility with existing systems, data privacy, and concerns about legal implications.

Artificial intelligence offers significant potential to tackle FW in the hospitality industry. However, overcoming knowledge gaps, addressing scepticism, and ensuring affordability are crucial for wider adoption. This research emphasised the importance of educational resources and training programs to increase AI literacy within the hospitality sector. Promoting successful case studies and addressing data privacy concerns can further build trust and encourage adoption, especially among SMEs that dominate the industry.

Collaboration between stakeholders, including government, industry, and research institutions, is vital to foster AI innovation and develop affordable, user-friendly AI solutions.

By effectively utilising AI, the hospitality industry can achieve significant progress towards overall sustainability. We find that the hospitality industry in New Zealand is increasingly recognising the importance of sustainability, with a focus on both environmental responsibility and economic benefits. There is a range of priorities within the sector, suggesting a need for educational efforts to promote a more holistic approach to sustainability that incorporates environmental, economic, and social aspects. Reducing FW improves the environment by decreasing resource depletion and greenhouse gas emissions, and companies by increasing profits. Importantly, this research paves the way for a future where AI empowers the New Zealand hospitality sector to embrace sustainable practices and contribute to a more environmentally responsible future.

Limitations of the Study

One of the key limitations is the sampling methods used in the study - convenience and snowball sampling. While convenience sampling ensures efficient data collection, it might not be representative of the entire New Zealand hospitality industry. Snowball sampling has the potential to reach a more diverse sample, however, it also carries the risk of snowballing bias. This could further limit the generalisability of the findings. Moreover, non-random sampling restricts data analysis to descriptive statistical analysis, constricting avenues such as inferential data analysis, which aids in validating and generalising findings.

Sample size and representativeness are yet another limitation of this study. Our research focused on the entire country, however, over 80% of the responses received are from the North Island, primarily comprising Auckland and Wellington. While this represents a significant portion in terms of the market share and the number of outlets, a representative sample from the South Island, which holds roughly 20% of the market share, would have been ideal. This omission might overlook potential differences in AI awareness, waste management practices, and perceptions based on regional variations. Furthermore, while adequate for initial analysis, the chosen sample size of 150 participants (reduced sample size of 131) might not be sufficient to capture the full spectrum of experiences and perspectives within the industry. A larger sample size could provide a more robust understanding of stakeholder knowledge, perceptions and attitudes towards AI for FW reduction.

Another limitation of the study is that it primarily focused on FW reduction through AI implementation. While FW is a major concern, hospitality businesses also generate beverage waste. Excluding beverage waste from the research scope limits the overall picture of waste management practices and the potential impact of AI solutions. Future studies could explore beverage waste along with FW and AI applications for optimising beverage inventory management, forecasting demand, and potentially minimising beverage waste.

Finally, our study relied solely on a quantitative survey. While it is valuable for gathering data on knowledge, attitudes, and practices, it might lack the depth and degree often achieved through qualitative interviews. Future studies could explore a mixed method. Qualitative interviews can offer insights into stakeholder experiences and potential uses of AI for sustainability goals. Case studies on New Zealand hospitality businesses can explore AI technologies, integration processes, challenges, and impact on waste reduction and sustainability practices.

Future Directions

One of the key areas for further investigation is developing and evaluating targeted interventions to address the lack of awareness, scepticism, and implementation challenges related to AI in the hospitality industry. Our study identified these factors as key barriers to AI adoption. Directly targeting these issues would bridge the gap and promote their wider implementation.

Examining bias in AI-powered hospitality solutions is another potential area for investigation. Investigating how cultural preferences, dietary restrictions, and historical data patterns can influence AI recommendations in hospitality settings, along with developing methods to mitigate bias, ensures responsible AI development. It also prevents potential discrimination based on dietary needs or cultural background.

Exploring AI for a holistic view of sustainability would be another important area for research. Exploring how AI can be used to optimise energy and water consumption in kitchens, manage sustainable ingredient sourcing, and track the environmental impact of hospitality operations throughout the supply chain. This broadens the scope of AI's contribution to sustainability beyond FW reduction, encompassing a holistic approach throughout the hospitality industry's operations.

Recommendations

Artificial Intelligence adoption in New Zealand is slow due to scepticism and lack of awareness. Short-term efforts should focus on capacity building, raising awareness, and implementing pilot projects. On the other hand, long-term efforts should emphasise research and development, human-AI collaboration, and social and environmental sustainability of AI solutions.

To address scepticism, clear cost-benefit analyses tailored to the hospitality context are essential. Highlighting potential return on investment in terms of reduced FW, improved efficiency, and increased revenue can entice sceptical businesses. User-friendly information resources on AI for FW reduction should be developed, including explainer videos, case studies, and cost comparisons. Global Champions of 12.3 published business cases in 2018 and 2019 highlighting the benefits of reducing FW in various sectors, revealing average savings of $6-$7 per $1 invested (New Zealand Food Waste Champions 12.3 Trust, n.d.). Training programs for hospitality staff on AI applications related to FW reduction should also be explored.

Collaborating with industry leaders to showcase the effectiveness of AI solutions in real-world settings could enhance optimism and ready the industry to embrace AI solutions. Developing industry-wide best practices and government initiatives offering grants or tax breaks for SMEs adopting AI for FW reduction could significantly impact adoption rates in the short term.

In the long term, building trust in AI through transparency and explainability is crucial. Building user-friendly interfaces, addressing data privacy and security concerns, and demonstrating responsible data-sourcing practices can build trust in the long run.

Effective management of FW requires a combination of government regulations, technology, and the commitment of businesses and consumers (Singh et al., 2024). Collaborating with industry associations, universities, and research institutions can foster the development of cost-effective and user-friendly AI solutions tailored to the needs of New Zealand's hospitality industry. Addressing national AI understanding is crucial for creating confidence in AI implementation and equipping future generations with the knowledge and skills to navigate an increasingly AI-driven world.

References

Aamir, M., Ahmad, H., Javaid, Q., & Hasan, S. M. (2018). Waste Not, Want Not: A Case Study on Food Waste in Restaurants of Lahore, Pakistan. *Journal of Food Products Marketing*, *24*(5), 591–610. https://doi.org/10.1080/10454446.2018.1472695

Aci, M., & Yergök, D. (2023). Demand Forecasting for Food Production Using Machine Learning Algorithms: A Case Study of University Refectory. Scientific Paper, 30(ISSN 1330-3651), 1683–1691. https://doi.org/10.17559/TV-20230117000232

Afzal, N., Basit, A., Daniel, A., Ilyas, N., Imran, A., Awan, Z. A., Papargyropoulou, E., Stringer, L. C., Hashem, M., Alamri, S., Bashir, M. A., Li, Y., & Roy, N. (2022). Quantifying Food Waste in the Hospitality Sector and Exploring Its Underlying Reasons—A Case Study of Lahore, Pakistan. *Sustainability*, *14*(11), 6914. https://doi.org/10.3390/su14116914

Alhaddi, H. (2015). Triple Bottom Line and Sustainability: a Literature Review. Business and Management Studies, 1(2), 6–10. https://doi.org/10.11114/bms.v1i2.752

Amaro, A. C. S., Domingos, J. P. da S., & Marinho de Carvalho, J. (2021). Waste Control in a Catering Company. International Journal of Information Systems in the Service Sector, 13(2), 29–50. https://doi.org/10.4018/ijisss.2021040103

Amit, S. K., Uddin, Md. M., Rahman, R., Islam, S. M. R., & Khan, M. S. (2017). A review on mechanisms and commercial aspects of food preservation and processing. Agriculture & Food Security, 6(1). https://doi.org/10.1186/s40066-017-0130-8

Artash, A. (2022, April 22). 6 Examples of Zero Waste Restaurants and What They're Doing Right. EagleOwl - Restaurant Management and Analytics Software. https://eagleowl.in/w/4-ways-to-become-zero-waste-restaurant-in-2021/

Arvindaraj, G., Manikandan, B., Rokesh, R., & Abinaya, M. (2023, March 1). Opportunities of Machine Learning Techniques in the Catering Industry- A Survey. IEEE Xplore. https://doi.org/10.1109/ICEARS56392.2023.10085004

Atkinson, R., & Flint, J. (2001). Accessing Hidden and Hard-to-reach Populations: Snowball Research Strategies. Sociology at Surrey, 28(1), 93–108. https://www.researchgate.net/publication/46214232_Accessing_Hidden_and_Hard-to-Reach_Populations_Snowball_Research_Strategies

Baum, T. (2013, April 7). International perspectives on women and work in hotels, catering and tourism | International Labour Organization. Www.ilo.org. https://www.ilo.org/publications/international-perspectives-women-and-work-hotels-catering-and-tourism-0

Bellemare, M. F., Çakir, M., Peterson, H. H., Novak, L., & Rudi, J. (2017). On the Measurement of Food Waste. American Journal of Agricultural Economics, 99(5), 1148–1158. https://doi.org/10.1093/ajae/aax034

Ben Youssef, A., & Zeqiri, A. (2022). Hospitality Industry 4.0 and Climate Change. Circular Economy and Sustainability, 2. https://doi.org/10.1007/s43615-021-00141-x

Beretta, C., Stoessel, F., Baier, U., & Hellweg, S. (2013). Quantifying food losses and the potential for reduction in Switzerland. Waste Management, 33(3), 764–773. https://doi.org/10.1016/j.wasman.2012.11.007

Betz, A., Buchli, J., Göbel, C., & Müller, C. (2015). Food waste in the Swiss food service industry – Magnitude and potential for reduction. Waste Management, 35(35), 218–226. https://doi.org/10.1016/j.wasman.2014.09.015

Bhajan, C., Neetoo, H., Hardowar, S., Boodia, N., Driver, M. F., Chooneea, M., Ramaswamy, B., Goburdhun, D., & Ruggoo, A. (2022). Food waste generated by the Mauritian hotel industry. Tourism Critiques: Practice and Theory, 3(2). https://doi.org/10.1108/trc-04-2022-0010

Booking.com. (2022, April 14). Climate, Community and Choice: Booking.com Reveals the Trends Shaping Sustainable Travel in 2022. Climate, Community and Choice: Booking.com Reveals the Trends Shaping Sustainable Travel in 2022. https://globalnews.booking.com/climate-community-and-choice-bookingcom-reveals-the-trends-shaping-sustainable-travel-in-2022/

Boston Consulting Group. (2022, May 25). Closing the Food Waste Gap. BCG Global. https://www.bcg.com/featured-insights/closing-the-gap/food-waste

Braun, V., & Clarke, V. (2006). Using Thematic Analysis in Psychology. Qualitative Research in Psychology, 3(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Brauner, P., Hick, A., Philipsen, R., & Ziefle, M. (2023). What does the public think about artificial intelligence?—A criticality map to understand bias in the public perception of AI. Frontiers in Computer Science, 5. https://doi.org/10.3389/fcomp.2023.1113903

Buzby, J. C., Farah-Wells, H., & Hyman, J. (2014). The Estimated Amount, Value, and Calories of Postharvest Food Losses at the Retail and Consumer Levels in the United States. SSRN Electronic Journal, 121. https://doi.org/10.2139/ssrn.2501659

CEO Outlook Pulse. (2024, January 30). The CEO Imperative: How will CEOs respond to a new recession reality? Www.ey.com. https://www.ey.com/en_gl/ceo/ceo-outlook-global-report

Charlebois, S., Creedy, A., & von Massow, M. (2015). "Back of house" – focused study on food waste in fine dining: the case of Delish restaurants. *International Journal of Culture, Tourism and Hospitality Research*, *9*(3), 278–291. https://doi.org/10.1108/ijcthr-12-2014-0100

Chauhan, C., Dhir, A., Akram, M. U., & Salo, J. (2021). Food loss and waste in food supply chains. A systematic literature review and framework development approach. Journal of Cleaner Production, 295, 126438. https://doi.org/10.1016/j.jclepro.2021.126438

Cheng, I. K., & Leong, K. K. (2023). Data-driven decarbonisation pathways for reducing life cycle GHG emissions from food waste in the hospitality and food service sectors. Scientific Reports, 12(1), 1–17. https://doi.org/10.1038/s41598-022-27053-6

Chisnall, S. (2017). A TASTE FOR CONSUMPTION: Food Waste Generation in New Zealand Cafés and Restaurants. In https://ourarchive.otago.ac.nz/bitstream/handle/10523/7942/ChisnallSarahJ2017MDiet.pdf?sequence=1&isAllowed=y.

Chowdhury, M. F. (2014). Interpretivism in Aiding Our Understanding of the Contemporary Social World. Open Journal of Philosophy, 04(03), 432–438. researchgate. https://doi.org/10.4236/ojpp.2014.43047

Christine, C. S. M., & Latifah, A. M. (2022). MAKING A DECISION USING ANALYTICAL HIERARCHY PROCESS (AHP) IN SELECTING SUITABLE FOOD WASTE MANAGEMENT METHOD: A CONCEPTUAL FRAMEWORK. https://doi.org/10.17501/26510251.2022.31016

Chung, I., Gupta, A., & Tokunbo Ogunfunmi. (2022). Remote Crop Disease Detection Using Deep Learning with IoT. Scholar Commons (Santa Clara University). https://doi.org/10.1109/ghtc55712.2022.9910991

Damaren, P. (2023, September 11). 9 Ways AI Is a Game-Changer for the Hospitality Industry. Hospitality Technology. https://hospitalitytech.com/9-ways-ai-game-changer-hospitality-industry

Datacom. (n.d.). NZ Companies Split On AI adoption, Lack Of Policies Poses Risk. Datacom. https://datacom.com/nz/en/discover/articles/nz-companies-split-on-ai-adoption-lack-of-policies-poses-risk

Derqui, B., Fayos, T., & Fernandez, V. (2016). Towards a More Sustainable Food Supply Chain: Opening up Invisible Waste in Food Service. Sustainability, 8(7), 693. https://doi.org/10.3390/su8070693

Dhir, A., Talwar, S., Kaur, P., & Malibari, A. (2020). Food Waste in Hospitality and Food Services: A Systematic Literature Review and Framework Development Approach. Journal of Cleaner Production, 270, 122861. https://doi.org/10.1016/j.jclepro.2020.122861

DKube Inc. (2023, October 31). Modern Hoteliers - Why are they slow in adoption of technology? Www.linkedin.com. https://www.linkedin.com/pulse/modern-hoteliers-why-slow-adoption-technology-dkube-tm4cc/?trk=public_post_main-feed-card_reshare_feed-article-content

Dombroski, S. (2023, September 19). The benefits of AI in food manufacturing and the supply chain. Www.foodprocessing.com.au. https://www.foodprocessing.com.au/content/materials-handling-storage-and-supply-chain/article/the-benefits-of-ai-in-food-manufacturing-and-the-supply-chain-244119925

Duppati, G., Scrimgeour, F., Chancharat, S., & Kijkasiwat, P. (2021). Ethnic diverse and financing choices affecting of business survival: a case study of New Zealand small- and medium-sized enterprises. *Journal of Economics, Finance and Administrative Science*, *26*(51), 160–174. https://doi.org/10.1108/jefas-11-2019-0270

Eriksson, M., Malefors, C., Callewaert, P., Hartikainen, H., Pietiläinen, O., & Strid, I. (2019). What gets measured gets managed – Or does it? Connection between food waste quantification and food waste reduction in the hospitality sector. Resources, Conservation & Recycling: X, 4, 100021. https://doi.org/10.1016/j.rcrx.2019.100021

Faezirad, M., Pooya, A., Naji-Azimi, Z., & Amir Haeri, M. (2021). Preventing food waste in subsidy-based university dining systems: An artificial neural network-aided model under uncertainty. Waste Management & Research: The Journal for a Sustainable Circular Economy, 39(8), 1027–1038. https://doi.org/10.1177/0734242x211017974

Farinella, L., Fernandes, E., Michener, N., Polimeni, M., & Vesonder, G. (2020). Identification of Food Waste through Object Recognition. 2020 11th IEEE Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON). https://doi.org/10.1109/uemcon51285.2020.9298165

Filimonau, V., & De Coteau, D. A. (2019). Food waste management in hospitality operations: A critical review. Tourism Management, 71, 234–245. https://doi.org/10.1016/j.tourman.2018.10.009

Filimonau, V., Chiang, C.-C., Wang, L., Muhialdin, B. J., & Ermolaev, V. A. (2023). Resourcefulness of chefs and food waste prevention in fine dining restaurants. International Journal of Hospitality Management, 108, 103368. https://doi.org/10.1016/j.ijhm.2022.103368

Filimonau, V., Fidan, H., Alexieva, I., Dragoev, S., & Marinova, D. D. (2019). Restaurant food waste and the determinants of its effective management in Bulgaria: An exploratory case study of restaurants in Plovdiv. Tourism Management Perspectives, 32, 100577. https://doi.org/10.1016/j.tmp.2019.100577

Filimonau, V., Krivcova, M., & Pettit, F. (2019). An exploratory study of managerial approaches to food waste mitigation in coffee shops. International Journal of Hospitality Management, 76, 48–57.

Fletcher, M. & Rasmussen, E. (2020). 'Commentary: Labour market change and employee protection in light of the 'Future of Work' debate.' New Zealand Journal of Employment Relations, 44(3): 32-44

Garre, A., Ruiz, M. C., & Hontoria, E. (2020). Application of Machine Learning to support production planning of a food industry in the context of waste generation under uncertainty. Operations Research Perspectives, 7, 100147. https://doi.org/10.1016/j.orp.2020.100147

Gerlich, M. (2023). Perceptions and Acceptance of Artificial Intelligence: A Multi-Dimensional Study. Social Sciences, 12(9), 502. https://doi.org/10.3390/socsci12090502

Goldenberg, S. (2018, February 14). From field to fork: the six stages of wasting food. The Guardian; The Guardian. https://www.theguardian.com/environment/2016/jul/14/from-field-to-fork-the-six-stages-of-wasting-food

Golzar, J., Tajik, O., & Noor, S. (2022, December 16). Convenience Sampling. Https://Www.researchgate.net/Publication/366390016_Convenience_Sampling; International Journal of Education and Language Studies. doi: 10.22034/ijels.2022.162981

Gondaliya, S. H., & Sharma, A. K. (2023, May 1). A Review: Artificial Intelligence in Restaurant Business. Www.atlantis-Press.com; Atlantis Press. https://doi.org/10.2991/978-94-6463-136-4_33

Goodman-Smith, F., Bhatt, S., Moore, R., Mirosa, M., Ye, H., Deutsch, J., & Suri, R. (2021). Retail Potential for Upcycled Foods: Evidence from New Zealand. Sustainability, 13(5), 2624. https://doi.org/10.3390/su13052624

Goodman-Smith, F., Mirosa, M., & Skeaff, S. (2020). A mixed-methods study of retail food waste in New Zealand. Food Policy, 92, 101845. https://doi.org/10.1016/j.foodpol.2020.101845

Gosling, S. D., Vazire, S., Srivastava, S., & John, O. P. (2004). Should We Trust Web-Based Studies? A Comparative Analysis of Six Preconceptions About Internet Questionnaires. American Psychologist, 59(2), 93–104. https://doi.org/10.1037/0003-066x.59.2.93

Goyal, A., & Singh, N. P. (2021). Consumer perception about fast food in India: an exploratory study. British Food Journal, 109(2), 182–195. https://doi.org/10.1108/00070700710725536

Great Western Recycling. (2022, May 27). How to Reduce Food Waste in the Catering Industry. Great Western Recycling. https://www.greatwesternrecycling.co.uk/reduce-food-waste/

Griffin, M., Sobal, J., & Lyson, T. A. (2008). An analysis of a community food waste stream. Agriculture and Human Values, 26(1-2), 67–81. https://doi.org/10.1007/s10460-008-9178-1

Gunders, D. (2019, January 28). Wasted: How America Is Losing Up to 40 Percent of Its Food from Farm to Fork to Landfill. NRDC. https://www.nrdc.org/resources/wasted-how-america-losing-40-percent-its-food-farm-fork-landfill

Gustavsson, J., Cederberg, C., Sonesson, U., & Van Otterdijk, R. (2011). (PDF) Global Food Losses and Food Waste- Extent, Causes and Prevention. ResearchGate. https://www.researchgate.net/publication/285683189_Global_Food_Losses_and_Food_Waste-_Extent_Causes_and_Prevention

Harshini, K., Madhira, P. K., Chaitra, S., & Reddy, G. P. (2021, September 1). Enhanced Demand Forecasting System For Food and Raw Materials Using Ensemble Learning. IEEE Xplore. https://doi.org/10.1109/AIMV53313.2021.9671005

Heikkilä, L., Reinikainen, A., Katajajuuri, J.-M., Silvennoinen, K., & Hartikainen, H. (2016). Elements affecting food waste in the food service sector. Waste Management, 56, 446–453. https://doi.org/10.1016/j.wasman.2016.06.019

Hemmington, N. (2007). From Service to Experience: Understanding and Defining the Hospitality Business. The Service Industries Journal, 27(6), 747–755. https://doi.org/10.1080/02642060701453221

Hennayaka H. M.H. H, Dissanayaka D. M.I. S, Silva, Sakuntha N. M. K, Dassanayake D.M.G. T, & Jayasinghe J.A.D.T. B. (2022). AGventure: Creating a Sustainable Economy by Reducing Food Surpluses and Food Wastages through the Crop Management. 2022 IEEE 7th International Conference for Convergence in Technology (I2CT). https://doi.org/10.1109/i2ct54291.2022.9825094

Henrichs, E., & Krupitzer, C. (2022). Towards Adaptive, Real-Time Monitoring of Food Quality Using Smart Sensors. https://doi.org/10.1109/acsosc56246.2022.00034

Hinish, S. (2023, December 5). How AI can help accelerate the pace of change. Www.ey.com. https://www.ey.com/en_lu/sustainability/how-can-ai-help-us-accelerate-the-pace-of-change-the-world-needs

Hong, I., Park, S., Lee, B., Lee, J., Jeong, D., & Park, S. (2014). IoT-Based Smart Garbage System for Efficient Food Waste Management. The Scientific World Journal, 2014, 1–13. https://doi.org/10.1155/2014/646953

Hotel Technology News. (2023, October 1). Global Hotel Companies Are Deploying AI Technologies to Reduce Food Waste |. Hotel Technology News. https://hoteltechnologynews.com/2023/09/global-hotel-companies-are-deploying-ai-technologies-to-reduce-food-waste/

IATA. (2022). Sustainable Cabin: Cabin Waste and Single Use Plastics (SUP) Fact Sheet Cabin Waste Background. https://www.iata.org/en/iata-repository/pressroom/fact-sheets/fact-sheet---cabin-waste/

Infometrics. (2021). Economic impact of the New Zealand hospitality sector for Hospitality New Zealand. https://www.foodticker.co.nz/wp-content/uploads/2021/12/Economic-impact-of-the-New-Zealand-hospitality-sector-Hospitality-New-Zealand.pdf

Ipsos. (2023). A 31-country Global Advisor survey: GLOBAL VIEWS ON A.I. IN 2023. https://www.ipsos.com/sites/default/files/ct/news/documents/2023-07/Ipsos%20Global%20AI%202023%20Report%20-%20NZ%20Release%2019.07.2023.pdf

Jagtap, S., Bhatt, C., Thik, J., & Rahimifard, S. (2019). Monitoring Potato Waste in Food Manufacturing Using Image Processing and Internet of Things Approach. Sustainability, 11(11), 3173. https://doi.org/10.3390/su11113173

Johansson, A. (2023, July 18). How to Overcome the Challenges of AI Adoption in the Hotel Industry. Www.demandcalendar.com. https://www.demandcalendar.com/blog/how-to-overcome-the-challenges-of-ai-adoption-in-the-hotel-industry#:~:text=Data%20is%20fundamental%20for%20AI&text=The%20fundamentals%20of%20being%20able

Jones, E. (2017). An investigation into food waste produced in New Zealand restaurants and cafes. https://ourarchive.otago.ac.nz/bitstream/handle/10523/7924/JonesEmily2017MDiet.pdf?isAllowed=y&sequence=1

Kallbekken, S., & Sælen, H. (2013). "Nudging" hotel guests to reduce food waste as a win–win environmental measure. Economics Letters, 119(3), 325–327. https://doi.org/10.1016/j.econlet.2013.03.019

Kantar (2023). Rabobank - KiwiHarvest New Zealand Food Waste Survey. www.rabobank.co.nz. https://www.rabobank.co.nz/content/ranz/nz/en/community/food-waste.html

Karakas, K. M. (2021). Food Waste Management in Luxury Hotels—Best Practices and Limitations. *Journal of Environmental Science and Engineering B*, *10*(3). https://doi.org/10.17265/2162-5263/2021.03.003

Karamchandani, S., Sekhani, B., Nair, K., & Shah, K. (2021, September 1). E-nose for Shelf-Life Prediction of Climacteric Fruits. IEEE Xplore. https://doi.org/10.1109/GUCON50781.2021.9573573

Kasavan, S., Mohamed, A. F., & Abdul Halim, S. (2019). Drivers of food waste generation: Case study of island-based hotels in Langkawi, Malaysia. Waste Management, 91, 72–79. https://doi.org/10.1016/j.wasman.2019.04.055

Kelley, K., Clark, B., Brown, V., & Sitzia, J. (2003). Good practice in the conduct and reporting of survey research. International Journal for Quality in Health Care, 15(3), 261–266. OUP. https://doi.org/10.1093/intqhc/mzg031

Kelly, S., Kaye, S.-A., & Oviedo-Trespalacios, O. (2022). What Factors Contribute to Acceptance of Artificial Intelligence? A Systematic Review. Telematics and Informatics, 77(77), 101925. https://doi.org/10.1016/j.tele.2022.101925

Koivunen, L., Laato, S., Rauti, S., Naskali, J., Nissila, P., Ojansivu, P., Makila, T., & Norrdal, M. (2020). Increasing Customer Awareness on Food Waste at University Cafeteria with a Sensor-Based Intelligent Self-Serve Lunch Line. 2020 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC), Engineering, Technology and Innovation (ICE/ITMC), 2020 IEEE International Conference On, 1–9. https://doi.org/10.1109/ICE/ITMC49519.2020.9198571

Konfo, T. R. C., Djouhou, F. M. C., Hounhouigan, M. H., Dahouenon-Ahoussi, E., Avlessi, F., & Sohounhloue, C. K. D. (2023). Recent advances in the use of digital technologies in agri-food processing: A short review. Applied Food Research, 3(2), 100329. https://doi.org/10.1016/j.afres.2023.100329

Kuleshov, V., Seymour, H., Nemer, D., Meador, S., Fenner, N., & Schwartz, M. (2019). Towards a Sustainable Food Supply Chain Powered by Artificial Intelligence. https://www.cs.cornell.edu/~kuleshov/papers/icml2019-climate.pdf

Kumar, I., Rawat, J., Mohd, N., & Husain, S. (2021). Opportunities of Artificial Intelligence and Machine Learning in the Food Industry. Journal of Food Quality, 2021, 1–10. hindawi. https://doi.org/10.1155/2021/4535567

Kumar, N., Balasubramaniam, S., R.S, S. T., Kumar, P., & Janavi, B. (2020, July 1). An Autonomous Food Wastage Control Warehouse: Distributed Ledger and Machine Learning based Approach. IEEE Xplore. https://doi.org/10.1109/ICCCNT49239.2020.9225525

Kumar, T. B., Prashar, D., Vaidya, G., Kumar, V., Kumar, S. D., & Sammy, F. (2022). A Novel Model to Detect and Classify Fresh and Damaged Fruits to Reduce Food Waste Using a Deep Learning Technique. Journal of Food Quality, 2022, e4661108. https://doi.org/10.1155/2022/4661108

Ladd, T. (2023, August 25). For AI, Does Company Size Matter? Forbes. https://www.forbes.com/sites/tedladd/2023/08/25/for-ai-does-company-size-matter/?sh=559f337a2815

Lamba, M. (2021). Using Artificial Intelligence to Reduce Food Waste in United Arab Emirates. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3957401

Lee, H.-H., & Huang, P.-Y. (2023). Food Waste and Environmental Sustainability of the Hotel Industry in Taiwan. Sustainability, 15(21), 15459. https://doi.org/10.3390/su152115459

Leedy, P., & Ormrod, J. E. (2016). Practical research : planning and design (11th ed.). Pearson Education Limited.

Lewis, J. (2022, October 17). How Does Food Waste Affect the Environment. Earth.org. https://earth.org/how-does-food-waste-affect-the-environment/

Li, J. (Justin), Bonn, M.A. and Ye, B.H. (2019). Hotel employee's artificial intelligence and robotics awareness and its impact on turnover intention: The moderating roles of perceived organizational support and competitive psychological climate. Tourism Management, 73, pp.172–181.

Lim, V., Bartram, L., Funk, M., & Rauterberg, M. (2021). Eco-Feedback for Food Waste Reduction in a Student Residence. Frontiers in Sustainable Food Systems, 5. https://doi.org/10.3389/fsufs.2021.658898

Maguire, M., & Delahunt, B. (2017). Doing a thematic analysis: A practical, step-by-step guide for learning and teaching scholars. AISHE-J: The All Ireland Journal of Teaching and Learning in Higher Education, 9(3). http://ojs.aishe.org/index.php/aishe-j/article/view/335

Mainvil, L., Mirosa, M., Chisnall, S. J., Jones, E., Marshall, J., Wassilak, C., & WasteMINZ. (2018). Food Waste in the Cafe & Restaurant: Sector in New Zealand. https://ourarchive.otago.ac.nz/bitstream/handle/10523/12171/New-Zealand-cafe-and-resturant-food-waste-WasteMINZ-2018.pdf?sequence=1&isAllowed=y

Malefors, C., Callewaert, P., Hansson, P.-A., Hartikainen, H., Pietiläinen, O., Strid, I., Strotmann, C., & Eriksson, M. (2019). Towards a Baseline for Food-Waste Quantification in the Hospitality Sector—Quantities and Data Processing Criteria. Sustainability, 11(13), 3541. https://doi.org/10.3390/su11133541

Mannette, J. (2020). Food Security in Urban New Zealand: Food Waste, Food Utopias, and Food Values. https://doi.org/10.20381/ruor-24616

Marthinsen, J., MinisterrådN., & RådN. (2012). Prevention of food waste in restaurants, hotels, canteens and catering. Nordisk Ministerråd.

Martin-Rios, C., Demen-Meier, C., Gössling, S., & Cornuz, C. (2018). Food waste management innovations in the food service industry. Waste Management, 79, 196–206. https://doi.org/10.1016/j.wasman.2018.07.033

Martin-Rios, C., Hofmann, A., & Mackenzie, N. (2020). Sustainability-Oriented Innovations in Food Waste Management Technology. Sustainability, 13(1), 210. https://www.mdpi.com/2071-1050/13/1/210

Mavani, N. R., Ali, J. M., Othman, S., Hussain, M. A., Hashim, H., & Rahman, N. A. (2021). Application of artificial intelligence in food industry—a guideline. Food Engineering Reviews, 14(1), 134–175. https://doi.org/10.1007/s12393-021-09290-z

McAdams, B., von Massow, M., Gallant, M., & Hayhoe, M.-A. (2019). A cross industry evaluation of food waste in restaurants. Journal of Foodservice Business Research, 22(5), 449–466. https://doi.org/10.1080/15378020.2019.1637220

McKinsey & Company. (2023, April 24). What is AI? Www.mckinsey.com; McKinsey & Company. https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-is-ai

Mihirsen, D., Joseph, J. T., & Renisha, B. (2020, October 1). Time Series Analysis for Supply Chain Planning in Restaurants. IEEE Xplore. https://doi.org/10.1109/ICCCS49678.2020.9276872

Mills, B., O'Brien, R., Mirosa, M., & Skeaff, S. (2023). Food waste initiatives in the tertiary sector in Aotearoa New Zealand. Pūhau Ana Te Rā Tailwinds, 1(2). https://doi.org/10.11157/patr.v1i1.23

Ministry for Environment. (2022, March 13). Reducing food waste. Ministry for the Environment. https://environment.govt.nz/what-government-is-doing/areas-of-work/waste/reducing-food-waste/

Ministry of Business, Innovation & Employment. (2022). A RESEARCH REPORT ON TOURISM AND HOSPITALITY EMPLOYMENT CONDITIONS IN NEW ZEALAND. https://www.mbie.govt.nz/assets/research-report-tourism-hospitality-conditions-nz.pdf

Ministry of Business, Innovation & Employment. (2024). Services (featuring in-depth work on hospitality) | Ministry of Business, Innovation & Employment. Govt.nz. https://www.mbie.govt.nz/business-and-employment/employment-and-skills/regional-skills-leadership-groups/tamaki-makaurau/regional-workforce-plans/regional-workforce-plan/our-economy-industry-and-business/services

Morol, Md. K., Rokon, Md. S. J., Hasan, I. B., Saif, A. M., Khan, R. H., & Das, S. S. (2022). Food Recipe Recommendation Based on Ingredients Detection Using Deep Learning. Proceedings of the 2nd International Conference on Computing Advancements. https://doi.org/10.1145/3542954.3542983

Mouysset, C. (2023, April 28). 15 Emerging Technologies Helping Reduce Food Waste. Lightspeed POS; Lightspeed POS. https://www.lightspeedhq.com/blog/food-waste-emerging-technologies/

Mrowinski, B., Brougham, D., & Tappin, D. (2020). Managers' Perceptions of Artificial Intelligence and Automation: Insights into the Future of Work. New Zealand Journal of Employment Relations, 44(3): 76-91. https://www.nzjournal.org/NZJER44%283%29.pdf#page=77

Munir, M. T., Mohaddespour, A., Nasr, A. T., & Carter, S. (2021). Municipal solid waste-to-energy processing for a circular economy in New Zealand. Renewable and Sustainable Energy Reviews, 145, 111080. https://doi.org/10.1016/j.rser.2021.111080

Nadkarni, S., Kriechbaumer, F., Christodoulidou, N., & Rothenberger, M. (2023). Industry 4.0 applications towards sustainability in hospitality: First waves in the guest room. Journal of Global Business Insights, 8(1), 31–48. https://doi.org/10.5038/2640-6489.8.1.1216

National Restaurant Association. (2021, October 21). Rising food costs and supply chain issues are creating challenges. NRA. https://restaurant.org/education-and-resources/resource-library/rising-food-costs-and-supply-chain-issues-are-creating-challenges/

National Restaurant Association. (2021, October 21). Rising food costs and supply chain issues are creating challenges. NRA. https://restaurant.org/education-and-resources/resource-library/rising-food-costs-and-supply-chain-issues-are-creating-challenges/

New Zealand Food Waste Champions 12.3 Trust. (n.d.). Resources. NZ Champions 12.3. Retrieved April 26, 2024, from https://www.nzchampions123.org/resources

OECD. (2018). OECD Tourism Trends and Policies 2018. https://www.oecd.org/cfe/tourism/2018-Tourism-Trends-Policies-Highlights-ENG.pdf

Onyeaka, H., Tamasiga, P., Nwauzoma, U. M., Miri, T., Juliet, U. C., Nwaiwu, O., & Akinsemolu, A. A. (2023). Using Artificial Intelligence to Tackle Food Waste and Enhance the Circular Economy: Maximising Resource Efficiency and Minimising Environmental Impact: A Review. Sustainability, 15(13), 10482. https://doi.org/10.3390/su151310482

Palm, L. (2023, September 29). How AI can reduce food waste in foodservice | KTCHNrebel. Www.ktchnrebel.com. https://www.ktchnrebel.com/food-waste-in-the-gastronomy-industry/

Papargyropoulou, E., Lozano, R., K. Steinberger, J., Wright, N., & Ujang, Z. bin. (2014). The food waste hierarchy as a framework for the management of food surplus and food waste. Journal of Cleaner Production, 76(76), 106–115.

Papargyropoulou, E., Steinberger, J. K., Wright, N., Lozano, R., Padfield, R., & Ujang, Z. (2019). Patterns and Causes of Food Waste in the Hospitality and Food Service Sector: Food Waste Prevention Insights from Malaysia. Sustainability, 11(21), 6016. https://doi.org/10.3390/su11216016

Parfitt, J., Barthel, M., & Macnaughton, S. (2010). Food waste within food supply chains: quantification and potential for change to 2050. Philosophical Transactions of the Royal Society B: Biological Sciences, 365(1554), 3065–3081. https://doi.org/10.1098/rstb.2010.0126

Park, Y. S., Konge, L., & Artino, A. R. (2020). The Positivism Paradigm of Research. Academic Medicine, 95(5), 690–694. Researchgate. https://doi.org/10.1097/ACM.0000000000003093

Pirani, S. I., & Arafat, H. A. (2016). Reduction of food waste generation in the hospitality industry. Journal of Cleaner Production, 132, 129–145. https://doi.org/10.1016/j.jclepro.2015.07.146

Poon, L. (2019). When Food Is Too Good To Waste, College Kids Pick Up The Scraps. Npr.org. https://www.npr.org/sections/thesalt/2015/02/27/389284061/when-food-is-too-good-to-waste-college-kids-pick-up-the-scraps

Porter, S. D., Reay, D. S., Bomberg, E., & Higgins, P. (2018). Avoidable food losses and associated production-phase greenhouse gas emissions arising from application of cosmetic standards to fresh fruit and vegetables in Europe and the UK. Journal of Cleaner Production, 201, 869–878. https://doi.org/10.1016/j.jclepro.2018.08.079

Potinteu, A. E., Renftle, D., & Said, N. (2023). What Predicts AI Usage? Investigating the Main Drivers of AI Use Intention over Different Contexts. PsyArXiv (OSF Preprints). https://doi.org/10.31234/osf.io/jvdpe

Pounds, K., Bao, H., Luo, Y., De, J., Schneider, K., Correll, M., & Tong, Z. (2022). Real-Time and Rapid Food Quality Monitoring Using Smart Sensory Films with Image Analysis and Machine Learning. ACS Food Science & Technology, 2(7), 1123–1134. https://doi.org/10.1021/acsfoodscitech.2c00124

Principato, L., Marchetti, S., Barbanera, M., Luca Ruini, Capoccia, L., Comis, C., & Secondi, L. (2023). Introducing digital tools for sustainable food supply management: Tackling food loss and waste in industrial canteens. Journal of Industrial Ecology, 27(4), 1060–1075. https://doi.org/10.1111/jiec.13391

Principato, L., Pratesi, C. A., & Secondi, L. (2018). Towards Zero Waste: an Exploratory Study on Restaurant managers. International Journal of Hospitality Management, 74(1), 130–137. https://doi.org/10.1016/j.ijhm.2018.02.022

Pu, J., Zhu, S., Miao, Y., & Hua, H. (2022). Detection of dish waste degree based on image processing and convolutional neural networks. Environmental Progress & Sustainable Energy, 42(1). https://doi.org/10.1002/ep.13942

Rady, A., Dawood, A. E.-B., abo Taleb, M., & Adel, M. (2021). Food Waste in Hotel Restaurants: Causes, Reducing Practices and Barriers. Minia Journal of Tourism and Hospitality Research MJTHR, 12(1), 135–155. https://doi.org/10.21608/mjthr.2021.106361.1018

ReFED. (2016). The ReFED Inc Roadmap To Reducing Food Waste. Refed.org. https://refed.org/articles/the-refed-roadmap-to-reducing-food-waste/

Restaurant Association of New Zealand. (2023). Strategic projects. Restaurant Association of New Zealand. https://www.restaurantnz.co.nz/ra-advocacy/advocacy-strategic-projects/

Reynolds, C., Mirosa, M., & Clothier, B. (2016). New Zealand's Food Waste: Estimating the Tonnes, Value, Calories and Resources Wasted. Agriculture, 6(1), 9. https://doi.org/10.3390/agriculture6010009

Rodrigues, R. (2020). Legal and Human Rights Issues of AI: Gaps, Challenges and Vulnerabilities. Journal of Responsible Technology, 4(100005), 100005. sciencedirect. https://doi.org/10.1016/j.jrt.2020.100005

Roy, P., Ramaprasad, B. S., Chakraborty, M., Prabhu, N., & Rao, S. (2020). Customer Acceptance of Use of Artificial Intelligence in Hospitality Services: An Indian Hospitality Sector Perspective. Global Business Review, 097215092093975. https://doi.org/10.1177/0972150920939753

Ruel, H., & Njoku, E. (2020). AI redefining the hospitality industry. Journal of Tourism Futures, ahead-of-print(ahead-of-print). https://doi.org/10.1108/jtf-03-2020-0032

Sarapisto, T., Koivunen, L., Mäkilä, T., Klami, A., & Ojansivu, P. (2022). Camera-Based Meal Type and Weight Estimation in Self-Service Lunch Line Restaurants. https://doi.org/10.1109/icprs54038.2022.9854056

Sargisson, R. J., De Groot, J. I. M., & Steg, L. (2020). The Relationship Between Sociodemographics and Environmental Values Across Seven European Countries. Frontiers in Psychology, 11. https://doi.org/10.3389/fpsyg.2020.02253

Schmidt, K. (2019). Predicting the consumption of expired food by an extended Theory of Planned Behavior. Food Quality and Preference, 78, 103746. https://doi.org/10.1016/j.foodqual.2019.103746

Secondi, L., Principato, L., & Laureti, T. (2015). Household food waste behaviour in EU-27 countries: A multilevel analysis. Food Policy, 56, 25–40. https://doi.org/10.1016/j.foodpol.2015.07.007

Shanthini, K. M., P. Chitra, S. Abirami, G Aninthitha, & P. Abarna. (2021). Recommendation of Product Value by Extracting Expiry Date using Deep Neural Network. https://doi.org/10.1109/icccnt51525.2021.9579675

Sharma, P., Vimal, A., Vishvakarma, R., Kumar, P., de Souza Vandenberghe, L. porto, Kumar Gaur, V., & Varjani, S. (2022). Deciphering the blackbox of omics approaches and artificial intelligence in food waste transformation and mitigation. International Journal of Food Microbiology, 372, 109691. https://doi.org/10.1016/j.ijfoodmicro.2022.109691

Sharp, E. L., Haszard, J., Egli, V., Roy, R., Te Morenga, L., Teunissen, L., Decorte, P., Cuykx, I., De Backer, C., & Gerritsen, S. (2021). Less Food Wasted? Changes to New Zealanders' Household Food Waste and Related Behaviours Due to the 2020 COVID-19 Lockdown. Sustainability, 13(18), 10006. https://doi.org/10.3390/su131810006

Sileyew, K. J. (2019). Research Design and Methodology. Text Mining - Analysis, Programming and Application, 1–12. Researchgate. https://doi.org/10.5772/intechopen.85731

Singh, V., T. Archana, Singh, A., & Pankaj Kumar Tyagi. (2024). Utilizing Technology for Food Waste Management in the Hospitality Industry Hotels and Restaurants. Practice, Progress, and Proficiency in Sustainability (Print), 287–295. https://doi.org/10.4018/979-8-3693-2181-2.ch019

Smeesters, L., Magnus, I., Virte, M., Thienpont, H., & Meulebroeck, W. (2021). Potato quality assessment by monitoring the acrylamide precursors using reflection spectroscopy and machine learning. Journal of Food Engineering, 311, 110699–110699. https://doi.org/10.1016/j.jfoodeng.2021.110699

Snežana Janković, & Curovic, D. M. (2023). Strategic Integration of Artificial Intelligence for Sustainable Businesses: Implications for Data Management and Human User Engagement in the Digital Era. Sustainability, 15(21), 15208–15208. https://doi.org/10.3390/su152115208

Soltani, Z., Kresten Kjaer Soerensen, Leth, J., & Jan Dimon Bendtsen. (2021). Robustness analysis of PCA-SVM model used for fault detection in supermarket refrigeration systems *. 2021 International Conference on Electrical, Communication, and Computer Engineering (ICECCE). https://doi.org/10.1109/icecce52056.2021.9514086

Statista. (2023, September 13). Global market size of the hospitality industry 2020. Statista; www.statista.com. https://www.statista.com/statistics/1247012/global-market-size-of-the-hospitality-industry/

StatsNZ. (2020, August 21). Fewer women working in tourism industries | Stats NZ. Www.stats.govt.nz. https://www.stats.govt.nz/news/fewer-women-working-in-tourism-industries

Tatàno, F., Caramiello, C., Paolini, T., & Tripolone, L. (2017). Generation and collection of restaurant waste: Characterization and evaluation at a case study in Italy. Waste Management, 61, 423–442. https://doi.org/10.1016/j.wasman.2017.01.020

Teerlink, M. (2019, November 25). SAP BrandVoice: By Ending Food Waste, We Could Feed 10 Billion People. Forbes. https://www.forbes.com/sites/sap/2019/11/25/ending-food-waste-could-feed-10-billion-people/?sh=111e4da2159a

Tibay, V., Miller, J., Chang-Richards, A. (Yan), Egbelakin, T., Seville, E., & Wilkinson, S. (2018). Business resilience: A study of Auckland hospitality sector. *Procedia Engineering*, *212*, 1217–1224. https://doi.org/10.1016/j.proeng.2018.01.157

Tomaszewska, M., Bilska, B., Tul-Krzyszczuk, A., & Kołożyn-Krajewska, D. (2021). Estimation of the Scale of Food Waste in Hotel Food Services—A Case Study. Sustainability, 13(1), 421. https://doi.org/10.3390/su13010421

Ufot, J., Esterline, A., & Bryant, K. S. (2021, March 1). Inventory Control at a University Food Pantry Using an MVC Software Pattern and Data Visualisation. IEEE Xplore. https://doi.org/10.1109/SoutheastCon45413.2021.9401894

Uğur Genç, H., Yıldız, M., Yilmazer, H., & Coşkun, A. (2019). Stop Wasting, Start Tasting! Design Speculations for Reducing Food Waste in The Hospitality Sector. https://doi.org/10.1145/3301019.3323880

UNDP. (2023). Sustainable Development Goals. Sustainable Development Goals; United Nations. https://www.undp.org/sustainable-development-goals

United Nations. (2024). Sustainability. United Nations. https://www.un.org/en/academic-impact/sustainability#:~:text=In%201987%2C%20the%20United%20Nations

van der Walt, A., & Bean, W. L. (2022). Inventory management for the in-flight catering industry: A case of uncertain demand and product substitutability. Computers & Industrial Engineering, 165, 107914. https://doi.org/10.1016/j.cie.2021.107914

Varghese, C., Pathak, D., & Varde, A. S. (2021, January 1). SeVa: A Food Donation App for Smart Living. IEEE Xplore. https://doi.org/10.1109/CCWC51732.2021.9375945

Voukkali, I., Papamichael, I., Loizia, P., & Zorpas, A. A. (2023). The importance of KPIs to calibrate waste strategy in hospitality sector. Energy Nexus, 11, 100211. https://doi.org/10.1016/j.nexus.2023.100211

Wang, Y., & Yuan, Z. (2021). Enhancing food security and environmental sustainability: A critical review of food loss and waste management. Resources, Environment and Sustainability, 4(100023), 100023. https://doi.org/10.1016/j.resenv.2021.100023

Wansink, B., & van Ittersum, K. (2013). Portion size me: Plate-size induced consumption norms and win-win solutions for reducing food intake and waste. Journal of Experimental Psychology: Applied, 19(4), 320–332. https://doi.org/10.1037/a0035053

WasteMINZ. (2018). CAFE & RESTAURANT SECTOR IN NEW ZEALAND. https://lovefoodhatewaste.co.nz/wp-content/uploads/2022/05/New-Zealand-cafe-and-resturant-food-waste-WasteMINZ-2018.pdf

Wen, Z., Hu, S., De Clercq, D., Beck, M. B., Zhang, H., Zhang, H., Fei, F., & Liu, J. (2018). Design, implementation, and evaluation of an Internet of Things (IoT) network system for restaurant food waste management. Waste Management, 73, 26–38. https://doi.org/10.1016/j.wasman.2017.11.054

Wijaya, G. T., & Nugraha, I. G. D. (2021). Prediction system of chicken meat expiration time based on polynomial regression using NodeMCU ESP8266 and MQ137 sensor. AIP Conference Proceedings, Volume 2376, Issue 1, Article Id.040015. https://doi.org/10.1063/5.0064986

Williams, C. (2007). Research Methods. Journal of Business & Economics Research (JBER), 5(3). https://doi.org/10.19030/jber.v5i3.2532

Williams, P., Leach, B., Christensen, K., Armstron, G.D., Hawkins, R.P., Lane, A.J.G. and Scholes, P. (2011), The Composition of Waste Disposed of by the UK Hospitality Industry, Waste and Resources Action Programme, London, Report RES093-001

Woolley, E., Jellil, A., & Simeone, A. (2021). Wasting less food: smart mass customisation of food provision. Procedia CIRP, 96, 189–194. https://doi.org/10.1016/j.procir.2021.01.073

World Food Programme. (2020). 5 facts about food waste and hunger | World Food Programme. Www.wfp.org. https://www.wfp.org/stories/5-facts-about-food-waste-and-hunger

World Health Organisation. (2022, July 6). UN Report: Global hunger numbers rose to as many as 828 million in 2021. Www.who.int. https://www.who.int/news/item/06-07-2022-un-report--global-hunger-numbers-rose-to-as-many-as-828-million-in-2021#:~:text=The%20number%20of%20people%20affected

Wright, K. B. (2017). Researching Internet-Based Populations: Advantages and Disadvantages of Online Survey Research, Online Questionnaire Authoring Software Packages, and Web Survey Services. Journal of Computer-Mediated Communication, 10(3). Oxford Academic. https://doi.org/10.1111/j.1083-6101.2005.tb00259.x

Wu, Z., Mohammed, A., & Harris, I. (2021). Food waste management in the catering industry: Enablers and interrelationships. Industrial Marketing Management, 94, 1–18. https://doi.org/10.1016/j.indmarman.2021.01.019

Wunderlich, P., Pauli, D., Neumaier, M., Wisser, S., Hans-Jürgen Danneel, Volker Lohweg, & Dörksen, H. (2023). Enhancing Shelf Life Prediction of Fresh Pizza with Regression Models and Low Cost Sensors. Foods, 12(6), 1347–1347. https://doi.org/10.3390/foods12061347

Young, A. T., Amara, D., Bhattacharya, A., & Wei, M. L. (2021). Patient and general public attitudes towards clinical artificial intelligence: a mixed methods systematic review. The Lancet Digital Health, 3(9), e599–e611. https://doi.org/10.1016/s2589-7500(21)00132-1

Zhao, Y., & Dai, Z. (2023). Research on the influencing factors of food waste in colleges and universities under the background of dual carbon. https://doi.org/10.1117/12.2671940

Zhou, G., Chang, M., & Sun, Y. (2021). A Mobile Platform for Food Donation and Delivery System using AI and Machine Learning. Computer Science and Information Technology Trends. https://doi.org/10.5121/csit.2021.111715

Zingg, R., Andermatt, P., Mazloumian, A., & Rosenthal, M. (2021, October 29). Smart food waste management : embedded machine learning vs cloud based solutions. Digitalcollection.zhaw.ch; CEUR Workshop Proceedings. https://doi.org/10.21256/zhaw-23847

Zulhusni, M. (2022, December 14). AI adoption in A/NZ companies is slower than it is globally – What are they waiting for? Tech Wire Asia. https://techwireasia.com/12/2022/ai-adoption-in-a-nz-companies-is-slower-than-it-is-globally-what-are-they-waiting-for/

Appendix 1 – AI-Powered Applications

- Machine learning (ML) known to be the subset of AI is a computer algorithm that advances automatically with experiences (Mavani et al., 2021). ML is commonly used for complex tasks, large data sets, and variable combinations without pre-existing formulas. Further, it learns from examples instead of rules.
- The CV system (CVS) is a branch of AI that combines image processing and pattern recognition techniques (Mavani et al., 2021). In general, it comprised a digital camera, a lighting system, and software to process the images and carry out the analysis.
- Electronic nose (E-nose) is an instrument created to sense odours or flavours in analogy to the human nose. It consists of an array of electronic chemical sensors where it can recognise both simple and complex odours (Mavani et al., 2021).
- Electronic tongue (E-tongue) is an instrument that can determine and analyse taste (Mavani et al., 2021). E-tongue has been used to identify the ageing of flavour in beverages (Lan et al., 2017).

Appendix 2 - Artificial Intelligence-Driven Technologies in Supply Chain Management

Category	Description	Citations
Farm Management	AI helps in crop selection, seed selection, resource management through weather, soil & irrigation monitoring, disease detection & yield prediction.	Sharma et al., 2022; I. Kumar et al., 2021; T. Kumar et al., 2022; Chung et al., 2022; Hennayaka et al., 2022
Production and Processing	AI identifies production anomalies, detects unsuitable produce & tracks waste generation to improve efficiency and reduce waste.	Konfo et al., 2023; Garre et al., 2020; Smeesters et al., 2021; Jagtap et al., 2019
Intelligent Storage Systems	AI monitors food quality and shelf life through smart sensors and machine learning for informed decision-making.	Henrichs and Krupitzer, 2022; Pounds et al., 2022; N. Kumar et al., 2020
Supermarket Streamlining	AI automates supply chain decisions, improves expiry date management, monitors freshness, and optimises refrigeration systems to reduce waste.	Kuleshov et al., 2019; Shanthini et al., 2021; Wijaya and Nugraha, 2021; Karamchandani et al., 2021; Soltani et al., 2021
Empowering Households	AI helps consumers plan meals, track food maturity, and manage inventory to minimise household food waste.	Rezgui et al., 2020; Woolley et al., 2020; Lim et al., 2015

Appendix 3 - Artificial Intelligence-Driven Technologies in the Hospitality Industry

Category	Description	Citations
Smart Monitoring and Analytics	Sensors and AI analyse food quality, storage conditions, and expiration dates for proactive waste prevention.	Onyeaka et al., 2023
AI-Powered Dish Waste Detection	Image processing and deep learning identify and quantify dish waste in restaurants.	Pu et al., 2022
AI-Powered Food Intake Estimation	Cameras and computer vision estimate food intake to reduce waste and improve nutrition.	Sarapisto et al., 2022
Smart Dining Halls	Combine CNN image processing and data analysis to reduce waste in college dining.	Farinella et al., 2020
Smart Waste Management	IoT-based systems with sensors track waste generation and optimise management.	Wen et al., 2018; Hong et al., 2014
Intelligent Lunch Lines	Sensors track customer choices and bio-waste to reduce cafeteria waste.	Koivunen et al., 2020
Tracking Leftovers	AI analyses leftover plates to identify wasted food and inform menu planning.	Cheng and Leong, 2023

Category	Description	Citations
AI-Powered Predictive Analytics Tools	Analyse data to predict demand, optimise inventory, and minimise overproduction.	Onyeaka et al., 2023
Optimising Restaurant Inventory	Machine learning predicts raw material needs to reduce overstocking and waste.	Mihirsen et al., 2020
AI-Powered Ingredient Planning	AI suggests ingredients and recipes to reduce waste and costs.	Arvindaraj et al., 2023; Morol et al., 2022
AI-Powered Raw Material Requirement Prediction	AI predicts raw material needs to avoid spoilage and optimise purchasing.	Harshini et al., 2021
AI-Powered Food Freshness Prediction	Machine learning predicts food spoilage to optimise shelf life and reduce waste.	Wunderlich et al., 2023
Machine Learning for Pandemic Resilience	AI helps predict attendance and adjust food production in catering establishments.	Malefors et al., 2019
Machine Learning-Driven Demand Forecasting	Machine learning helps predict demand to reduce food waste in university restaurants.	Santos et al., 2021; Faezirad et al., 2021; Aci and Yergok, 2023; Li et al., 2019
AI-Driven Menu Design	AI analyses data and suggests menu items to prevent ingredient waste.	Uğur Genç et al., 2019
Real-Time Food Waste Monitoring	IoT system with AI monitors and analyses food waste in kitchens.	Zingg et al., 2021

Category	Description	Citations
AI-Generated Key Performance Indicators (KPIs)	AI helps analyse data and create dashboards to track and manage food waste.	Amaro et al., 2021
AI-Powered Demand Forecasting	AI forecasts demand to optimise food preparation and reduce waste.	Cheng and Leong, 2023
AI-Powered Inventory Management	AI optimises inventory levels to reduce spoilage and waste.	Onyeaka et al., 2023
Data-Driven Decision-Making in Food Pantries	An inventory tracking system with data visualisation optimises food management in pantries.	Ufot et al., 2021
AI-Driven Substitution Model	AI optimises inventory management for in-flight catering to reduce waste.	van der Walt and Bean, 2022
Artificial Intelligence for Consumer Awareness and Education	AI educates consumers on meal planning, storage, and waste reduction.	Onyeaka et al., 2023
Artificial Intelligence-Based Donations and Redistribution	AI matches food donors with those in need, reducing waste and hunger.	Onyeaka et al., 2023; Varghese et al., 2021; Zhou et al., 2021

Appendix 4 - Questionnaire

AI and Food Waste

Start of Block: Tell us about you!

Criteria Are you currently employed, or have you ever worked in the Hospitality Industry in New Zealand?
Yes (1)

No (2)

Display This Question:

If Are you currently employed, or have you ever worked in the Hospitality Industry in New Zealand? = Yes

Age Your Age
Under 25 (4)

25-34 (5)

35-44 (6)

45-54 (7)

55 or older (8)

Gender Your Gender
Male (1)

Female (2)

Other (3)

Prefer not to say (4)

Occupation Your occupation/role in the establishment
Owner/Manager (1)

Chef/Cook (2)

Food Service Manager (3)

Sustainability Manager (4)

Wait Staff (5)

Kitchen Staff (6)

Other (Please Specify) (7) ____

Experience Your experience in the Hospitality Industry
Less than 2 years (1)

2-5 years (2)

6-10 years (3)

More than 10 years (4)

End of Block: Tell us about you!

Start of Block: Tell us about your Establishment

Establishment type Your establishment
Fine dining restaurant (1)

Casual dining restaurant (2)

Fast food restaurant (3)

Hotel/Resort (4)

Catering service (5)

Cafe/Coffee shop (6)

Pub, Traven or a Bar (7)

Hospitality club (8)

Other (Please specify) (9) ____

Location Location of your establishment
Auckland (1)

Canterbury (2)

Wellington (3)

Waikato (4)

Rest of North Island (5)

Otago (6)

Bay of Plenty (7)

Rest of South Island (8)

Manawatu- Wanganui (9)

Other (Please specify) (10) ____

Employees Number of employees in your establishment
Less than 6 (1)

6-49 (2)

More than 50 (3)

Years in operation Number of years in operation
Less than 1 year (1)

1-5 years (2)

6-10 years (3)

More than 10 years (4)

End of Block: Tell us about your Establishment

Start of Block: Is there food waste in your Establishment?

Food waste percent Over the last week, what percentage of the food in your establishment ended up as waste?
Less than 10% (1)

10-19% (2)

20-29% (3)

30-39% (4)

Over 40% (5)

No waste (6)

Avoidable food waste Of the food waste generated in your establishment last week, what percentage could have been avoided with better practices or technology? ("Avoided" refers to any edible food that was thrown away)
Less than 10% (5)

10-19% (1)

20-39% (2)

40-59% (3)

Over 60% (4)

Unsure/Difficult to estimate (6)

Causes of food waste In your opinion, which of the following are the major contributors to food waste in your establishment? Please select and rank all that apply (1 star = lowest, 5 stars = highest).

Inaccurate demand forecasting (1)	☆	☆	☆	☆	☆
Portion control and plate waste (2)	☆	☆	☆	☆	☆
Inefficient inventory management and storage (4)	☆	☆	☆	☆	☆
Lack of food waste awareness/training (5)	☆	☆	☆	☆	☆
Supply chain challenges (7)	☆	☆	☆	☆	☆
Other (Please specify) (6)	☆	☆	☆	☆	☆

End of Block: Is there food waste in your Establishment?

Start of Block: How well do you know AI-driven technology for food waste reduction?

Familiarity overall Have you heard of or experienced any AI technologies specifically designed to reduce food waste in the Hospitality Industry?

Yes (1)

No (2)

Display This Question:

If Have you heard of or experienced any AI technologies specifically designed to reduce food waste i... = Yes

AI in industry If you selected yes, what are some examples of AI technologies that you have heard of or experienced being used in the Hospitality Industry to reduce food waste?

	Not at all familiar (1)	Moderately Familiar (2)	Very familiar (3)
Sensors and devices that identify food spoilage (1)			
Using cameras to track food waste in plates and bins (2)			
Intelligent kitchen management systems (3)			
Forecasting demand using machine learning (4)			
Smart bins that tell you how much food is wasted (5)			
Other (Please specify) (6)			

Display This Question:

If Have you heard of or experienced any AI technologies specifically designed to reduce food waste i... = No

Non-AI Strategies If you selected no, what methods are used to minimise food waste in your establishment? Please select all that apply.

Implementing food waste tracking system/Food waste audits (1)

Altering menu choices/portions (2)

Composting/Donating surplus food (3)

Educating staff and customers about food waste (4)

Inventory management software (5)

Other (Please specify) (6) ____

None (7)

End of Block: How well do you know AI-driven technology for food waste reduction?

Start of Block: What are your perceptions towards AI for food waste reduction?

Perception Do you believe that AI technologies have the potential to reduce food waste in the Hospitality Industry significantly?

Yes (73)

No (74)

Unsure (79)

Display This Question:

If Do you believe that AI technologies have the potential to significantly reduce food waste in the... = Yes

Benefits of AI What excites you about the potential of AI tools for reducing food waste in the Hospitality Industry. Please select all that apply.

Improved operational efficiency (1)

Data-driven decision making (2)

Real-time monitoring and alerts (3)

Cost savings and enhanced revenue (4)

Improved customer satisfaction (5)

Other (Please specify) (6) ____

Display This Question:

If Do you believe that AI technologies have the potential to significantly reduce food waste in the... = No

Challenges of AI What are some specific concerns you see in implementing AI tools for reducing food waste in your establishment? Please select your top THREE choices (1= highest, 3 = lowest).

______ Limited access to technology (1)
______ Data availability and quality of data (2)
______ Government regulations and data privacy laws (3)
______ Lack of awareness of AI solutions (4)
______ Skill gap, training needs and resistance to change (5)
______ Cost of implementation (8)
______ Other (Please specify) (7)

Display This Question:

If Do you believe that AI technologies have the potential to significantly reduce food waste in the... = Unsure

Skeptical of AI What information or evidence would help you feel more confident about AI's potential for reducing food waste in the Hospitality Industry? Please select all that apply.
Examples of successful AI implementations in similar businesses (1)

Data security and privacy guarantees of AI systems (2)

Clear cost-benefit analysis (3)

Information on user-friendly and affordable AI solutions (4)

Other (Please specify) (6) ____

End of Block: What are your perceptions towards AI for food waste reduction?

Start of Block: What are your attitudes and intentions in implementing AI tools to reduce food w

Interest How interested are you in implementing AI tools to reduce food waste in your hospitality business?
0 (0)

1 (1)

2 (2)

3 (3)

4 (4)

5 (5)

6 (6)

7 (7)

8 (8)

9 (9)

10 (10)

Implementation What factors would influence your decision to implement AI tools for food waste reduction? Please select your top THREE choices (1= highest, 3= lowest).
______ Proven effectiveness of AI in reducing food waste (1)
______ Cost-effectiveness (2)
______ Ease of implementation (3)
______ Compatibility with existing systems (4)
______ Other (Please specify) (6)
______ Not applicable as my organisation is not interested in applying AI tools (7)

Applications If you were to implement one AI solution tomorrow to address food waste in your establishment, what would it be?

AI-powered recipe scaling to minimise leftover ingredients (1)

Smart fridges/pantry systems for predicting spoilage and optimising usage (2)

Electronic noses and taste sensors for early detection of food spoilage (3)

Image analysis of food waste in plates and bins (4)

AI-powered demand forecasting software (7)

Other (Please specify) (5) ____

At this time, my organisation does not prioritise implementing AI tools (9)

Display This Question:

If If you were to implement one AI solution tomorrow to address food waste in your establishment, wh... = At this time, my organisation does not prioritise implementing AI tools

non-implementation If you choose not to implement AI tools shortly, what is the single biggest reason?

Limited access to technology infrastructure in my area (1)

Lack of well-organised data for AI analysis in my establishment (2)

Concerns about the costs of implementation and maintaining AI systems (3)

My business operation is too small to justify the investment in AI tools (4)

Other (Please specify) (5) ____

End of Block: What are your attitudes and intentions in implementing AI tools to reduce food w

---

Start of Block: Evaluating AI's contribution to broader sustainability goals

Sus-Benefits In your opinion, what potential benefits do you see in implementing AI technologies for food waste reduction in achieving the broader sustainability goals of your establishment? Please select your top THREE choices (1= highest, 3 = lowest).

______ Reducing environmental impact through resource conservation (1)
______ Enhancing community engagement and sustainability initiatives (2)
______ Improving brand reputation and customer perception (3)
______ Achieving cost savings and increased profitability (13)
______ Contributing to broader sustainability goals of the hospitality industry (14)
______ Other (Please specify) (15)
______ None (16)

End of Block: Evaluating AI's contribution to broader sustainability goals

Start of Block: General comments

General comments Tell us anything else you think we should know about your experience with AI for food waste management.

____

End of Block: General comments

Appendix 5– Ethics Approval

Research Ethics Application Approval

07 December 2023

Lead Researcher: Melanie Perera [redacted]
Co-Researchers:

Dear Melanie Perera [redacted]

Reference Number: AIC-RE-2023-14
Title of Application: Exploring the Role of AI in Enhancing Sustainability within New Zealand's Hospitality Industry: A Study on Knowledge, Applicability, and Perception in Reducing Food Waste

Thank you for your application for ethics approval for this project.
The review panel has considered your revised application including responses to questions and issues raised. We are pleased to inform you that we are satisfied with the revisions made and confirm ethical approval for the project.
Many thanks for your considered responses to our recommendations.
We wish you well with your work and remind you that at the conclusion of your research you should send a brief report with findings and /or conclusions to the Research Ethics Committee.
All correspondence regarding this application should include the reference number assigned.
Project approval is valid for three (3) years from date of letter.

With best regards,

Indrapriya Kularatne
Ethics Coordinator, Otago Polytechnic Auckland International Campus