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Literature Review

A WASTE REDUCTION JOURNEY: DATA-DRIVEN AND MACHINE LEARNING ON PERISHABLE FOOD WASTE OPTIMISATION IN NEW ZEALAND RETAIL SUPERMARKETS

Nenie Tamarisca Petrisia and Indrapriya Kularatne

OTAGO POLYTECHNIC AUCKLAND INTERNATIONAL CAMPUS

ABSTRACT

The issue of fresh food waste in retail supermarkets globally has become increasingly problematic, with New Zealand reporting alarming levels of waste primarily in vegetable, bakery, meat, fish, and fruit products. The retail supermarkets in NZ contribute more to food waste than any other sector, with an estimated 60,500 tonnes of food wasted annually due to customers' increasing expectations for fresh food, which is highly perishable. Despite numerous advanced technologies aimed at mitigating food waste, including deep learning techniques for fruit waste reduction and machine learning for food donation optimisation, perishable food waste remains a persistent challenge. This study employed a systematic literature review from scholarly journals to explore the potential of data-driven approaches combined with machine learning in preventing perishable food waste in retail supermarkets. The scholarly articles were extracted from online research databases. Drawing upon the principles of Sustainable Consumption and Production which aims to halve global food waste at the retail level and reduce waste through prevention strategies. This review focused on analysing existing research studies that investigated the application of machine learning for demand forecasting based on sales data and influencing parameters. Through a thematic analysis of the literature, this review identified key insights, challenges, and opportunities associated with implementing data-driven and machine learning strategies to mitigate perishable food waste in New Zealand retail supermarkets. By synthesising findings from the literature this study highlighted the urgency of the food waste prevention stage by utilising data-driven approach and machine learning for predicting accurate demand benefiting managers on fresh food purchase order decisions. Therefore, it helps improving operational outcomes, profitability, and customer satisfaction, specifically in lowering discarded unsold fresh food products.

Keywords: Data-driven, Machine Learning, Sustainability, Fresh food, Perishable food, Food waste reduction, Retail supermarkets.

INTRODUCTION

In retail supermarkets, providing fresh food is important due to the consumers' consideration to shop in supermarkets which have the best quality of fresh food products (Broekmeulen & Donselaar, 2019). The United Nations mentioned that an estimated 17% of food production is wasted in households, food service, and retail which has raised an issue about food systems sustainability and food insecurity (United Nations, 2024a). Furthermore, food waste production is closely connected to the increase of greenhouse gas emissions which leads to the contribution to the climate change problem (United Nations, 2024a). Research from University of Otago in New Zealand reported that retail supermarkets produced around 60,500 tonnes of food waste per annum (Goodman-Smith et al., 2020). It consisted of vegetable (27%) and bakery products (23%) as the highest amount of food wastage (Goodman-Smith et al., 2020; lovefoodhatewaste, 2020).

The Food and Agriculture Organisation of the United Nations (FAO) describes food waste as an appropriate food for human consumption being disposed of (either before or after the expiration date) (Food and Agriculture Organisation of the United Nations (FAO), 2013). Furthermore, food waste in retail supermarkets is caused by the shelf life, and supermarket standards for colour, shape and size, and variability (United Nations, 2020). According to Buisman, et al., (2019, p. 274), shelf life is defined as "the time between production and the use-by date". Short shelf-life products or fresh food, such as bakery products, fruit and vegetables, dairy products, poultry and fish, are part of the perishable food supplies which only have a maximum shelf life less than two weeks (Buisman, et al., 2019). These products need extra careful handling at the supply chain level where they often get damaged due to temperature changes, packaging, and delivery time (Haji et al., 2020). Therefore, perishable products contribute to the highest food waste production compared to preserved food (Riesenegger & Hübner, 2022). Advanced technologies have been used in solving the food waste problem in retail supermarkets. For instance, a product's expiration-date tracking through the implementation of Artificial Intelligence (AI) helps supermarkets to update the inventories (Li & Sun, 2022). Machine learning (ML) as part of AI has also supported the improvement of food waste prevention solutions. By integrating sales data with external factors such as store campaign, weather, events, and public holidays, ML can create accurate demand forecasts. This helps managers predict bakery production needs and perishable food orders for suppliers. (Glatzel et al., 2016). Therefore, technology makes it possible for retail supermarkets to achieve the goal of halving global food waste at retail level and reducing food waste at a prevention level as stated in Sustainable Development Goal, SDG 12, Responsible Consumption and Production, indicators (United Nations, 2024b).

Based on the above, this research aimed to explore the usage of a data-driven approach and ML to reduce food waste in retail supermarkets through current literature. The information from this research will be valuable for retail supermarkets in New Zealand, to increase the business revenue while achieving environmental, social, and governance (ESG) goals. Therefore, this research was driven by two research questions: (RQ 1) What are the challenges faced by retail supermarkets on perishable food wastage production? (RQ 2) What is the impact of the usage of a data-driven approach and ML on perishable food waste optimisation?

LITERATURE REVIEW

Perishable Food Waste Problem in Retail Supermarkets

Perishable food products are characterised by a short shelf-life which requires careful handling at supply chain level and warehouse management systems to prevent damage and spoilage, preserve availability and ensure revenue for the business (Haji et al., 2020; Maheshwari et al., 2021). These include bakery products, fruits and vegetables, dairy products, poultry and fish which require short delivery times, high-speed transportation, and streamlined handling processes to maintain the retail supermarket's quality standards of colour, shape and size (Dreyer et al., 2016; United Nations, 2020). In the New Zealand retail supermarket context, the research from University of Otago reported that vegetables are the highest number of products being discarded, which amounted to 27% annually. This is followed by bakery products (23%), poultry and fish (19%), and fruits (17%) (Goodman-Smith et al., 2020). This research collected the data from the main retail supermarket chains in New Zealand such as Pak'n'Save, New World, and Woolworths in Auckland, Wellington, Christchurch, and Dunedin using a mixed-methods approach which resulted in approximately 60,500 tonnes of food waste annually or 13 kg per capita (Goodman-Smith et al., 2020). A previous study conducted by Reynolds et al. (2016) in 2011 reported that fruit and vegetables with the total amount of 17,188 tonnes were being wasted from commercial and industrial. This is followed by other grocery categories; bakery products (6,305 tonnes), poultry and fish (30,373 tonnes), and dairy products (23,231 tonnes). The Input-Output Life-Cycle Assessment (IO-LCA) model estimated 70kg/year food waste generated per capita (Reynolds et al., 2016). Estimated food waste generated in the New Zealand supply chain were also calculated in FAO the report (FAO, 2013). Around 180 kg/year of food waste per capita was indicated in production to the retailing stage in North America and Oceania in which New Zealand is included in that country category (FAO, 2013). The report summarised that the cause of food waste in developed countries occurs at retail and consumer levels (FAO, 2011).

The contribution to food waste is caused by the interdependency between consumer demand and supermarkets (Teller et al., 2018). It is a challenge for retail supermarkets due to uncertain demand, and product quality standards for customers (Teller et al., 2018). This is also related to the strong competition which forces the supermarkets to meet the customers' expectations on product freshness, large product choice, and availability (Teller et al., 2018). Especially for the main retail supermarket chains, such as Pak'n'Save, Foodstuffs and Woolworths, producing more food waste happens when they need to meet the high quality standards of fruit, vegetables, and poultry based on colour, size, shape; and the standard of freshness by providing fresh bakery products every day (Goodman-Smith et al., 2020). However, one major challenge that arises around managing perishable food products is preventing spoilage and loss (Riesenegger & Hübner, 2022). Careful inventory management and logistical coordination are needed to ensure sales before the expiration date (Kazancoglu et al., 2022).

Despite changing and uncertain customer demand challenges, limited understanding of advanced technology becomes a barrier for each retail supermarket buyer to use predictive analysis and demand forecasting to reorder the goods (Teller et al., 2018). Lack of knowledge and training among retail supermarket buyers and staff regarding these advanced technologies can contribute to the increase of food waste. Without the proper usage of predictive analysis and forecasting tools, the main retail supermarket retailers might struggle to accurately anticipate demand patterns, leading to overstocking of products, mainly fresh food which ends up being discarded (Riesenegger & Hübner, 2022). These challenges can be overcome with the adoption and effective usage of advanced technology such as ML algorithms for demand forecasting in order to prevent food waste in which utilising data provides insight for retail supermarket buyers (Teller et al., 2018).

Data-Driven Approach and Machine Learning

Machine Learning has been widely implemented and used in the waste management field as waste prediction analysis of household waste, construction waste, post-disaster waste, biomass waste, and others (Li et al., 2023; Nagalli, 2022; Yazdani et al., 2024; Zaman, 2022). There has been previous research focusing on waste measurement and optimisation on perishable food in retail supermarkets. The findings revealed the suggested dynamic shelf life and dynamic pricing strategies to solve the perishable food waste problem (Buisman, et al., 2019; Kayikci et al., 2022; Ping et al., 2024). Several studies underline the importance of leveraging technology to address food waste challenges in retail supermarkets. Neural networks are highlighted as potential ML algorithms to deal with large-scale forecasting problems for perishable food (Ziegler, 2020). Similarly, a study conducted by Maheshwari et al., (2021) emphasised the usage of Internet of Things (IoT) to reduce the inventory cost for improved perishability performance leading to significant reduction in food waste. Therefore, this technological advance has evolved retail supermarket operations by using information systems to plan and reduce food waste. However, advanced data containing additional parameters such as promotions, special effects, and future events have not been yet available or used for food waste prevention systems (Riesenegger & Hübner, 2022).

According to Provost and Fawcett (2013), a data-driven approach emphasises the decision-making based on empirical evidence and insights derived from data analysis. Meanwhile, ML, as part of AI, also relies heavily on data to train the models and make predictions (Bishop, 2006). With the ML algorithm, it can learn from the data and complex patterns without relying on rule-based programming with 85% accuracy (Dangeti, 2017). Therefore, both the data-driven approach and ML leverage data in extracting meaningful patterns which drive the decision-making benefits for the retail supermarkets.

For ML algorithms to effectively find patterns and relationships, large volumes of data are required (Murphy, 2012). The data is typically split 50%, 25%, and 25% respectively for training, validation, and testing sets (Dangeti, 2017). The ML algorithms frequently need to be trained on both training and validation datasets in order to ensure validity (Dangeti, 2017). According to Hastie et al., (2009), ML algorithms use statistical approaches to analyse and make predictions autonomously. Consequently, the quantity and quality of available data have a significant impact on the model's performance (Goodfellow et al., 2016).

The first step in creating and implementing an ML model is gathering data, which is then prepared to fit the chosen ML algorithm (Dangeti, 2017). Data analysis reveals hidden links and patterns among variables (Dangeti, 2017). Three sets of data are separated out: test, validation, and training (Dangeti, 2017). The training data is subjected to ML algorithms, and in order to avoid overfitting, hyperparameters are adjusted using the validation set (Dangeti, 2017). In the final step, deployment is needed to classify outcomes in real-time streaming data (Dangeti, 2017). The ML capacity to find associations and hidden insights in massive datasets enables data-driven decision-making easier (Sarker, 2021). Retail supermarkets can identify trends, patterns, and irregularities in data analysis using ML algorithms that they might miss using the conventional methods (Goecks, 2020; Murphy, 2012). This facilitates the decision-making, streamlines workflow, and drives creativity within retail supermarkets (Goecks, 2020; Murphy, 2012). Furthermore, the mutually beneficial relationship between ML and data-driven approaches is strengthened by their iterative nature (Barber, 2012; Goodfellow et al., 2016). The ML functions as a feedback loop in which data is used to train models, predictions are made, and feedback is then used to enhance and optimise model performance (Goecks, 2020). This iterative method helps retail supermarkets to continuously adjust and improve their models depending on evolving data patterns and business requirements (Goecks, 2020). Thus, data-driven techniques and ML are related as ML functions as a strong tool to extract information from data, thereby enabling data-driven decision-making processes that will impact on the reduction of perishable food waste.

METHODOLOGY

A systematic literature review is defined as "a method for identifying, evaluating, and interpreting compatible research results related to research questions and specific topics or phenomena of concern" (Ibda et al., 2023, p. 288). In this article, the researchers have discussed the field of information systems in which combining computer science, business, and social science. Therefore, a systematic literature review was essential for this research to ensure reliable and reproducible findings derived from the analysis of primary studies (Ibda et al.,2023). A thorough literature review of information systems improves the quality and dependability of research outputs, contributing to the advancement of the field (Okoli & Schabram, 2010).

Search Strategy

A systematic search was performed to identify relevant articles published in databases from 2015 to 2024. The articles were extracted from Google and ProQuest databases. A detailed search strategy with keywords was used to ensure reproducibility and transparency (Ibda et al.,2023). Search terms, keywords, related to "perishable food waste", "fresh food", "food waste", "demand forecasting", "predictive analysis", "retail supermarkets", "data-driven", and "machine learning" to explore the potential of data-driven approaches combined with ML in preventing perishable food waste in retail supermarkets. There were 432 and 466 articles found in Google Scholar and ProQuest, respectively, using the keywords mentioned.

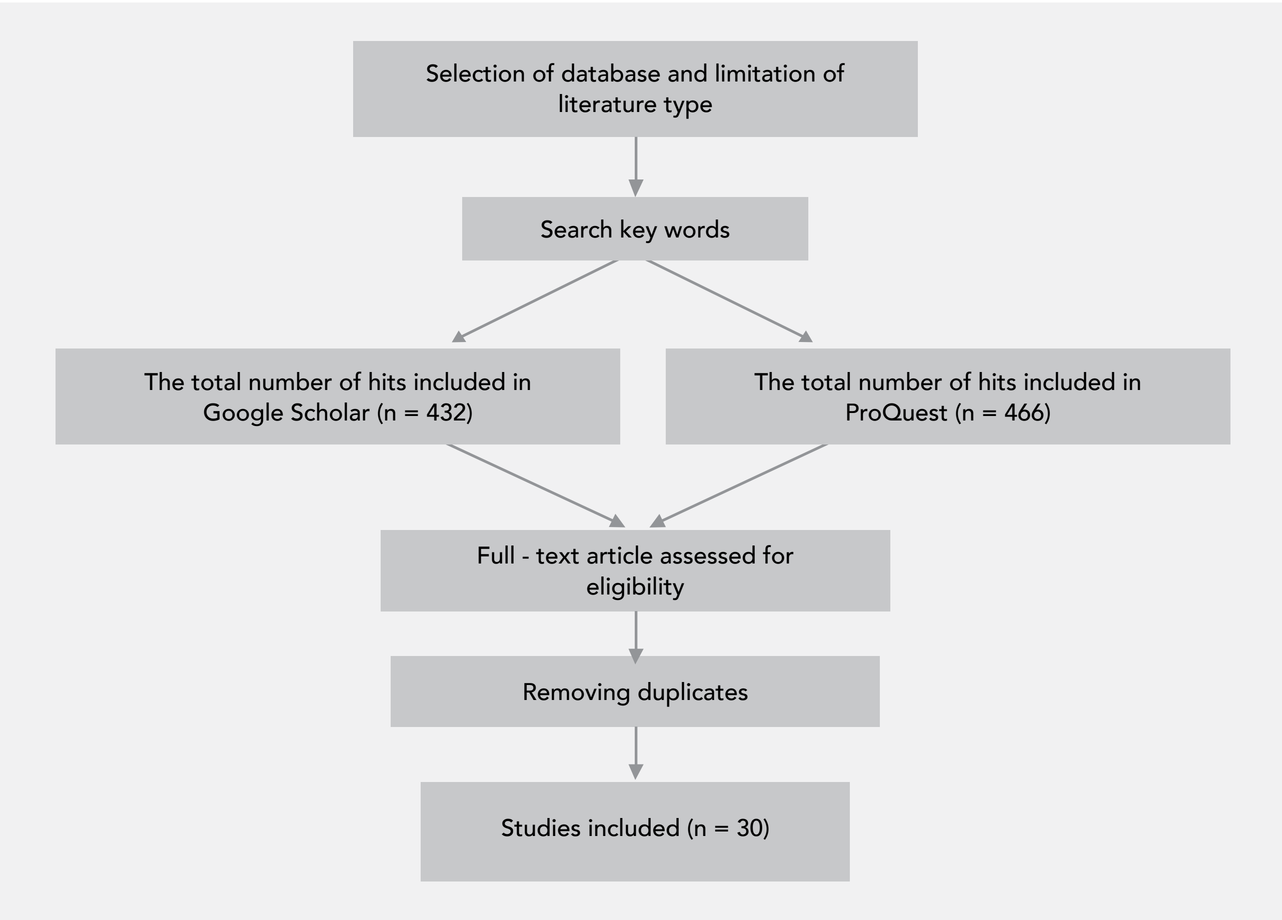
Inclusion and Exclusion Criteria for Selection

The research was limited to the criteria which is taken from Google Scholar and ProQuest database to determine whether all included articles were appropriate to answer RQ1: "What are the challenges faced by retail supermarkets on perishable food wastage production?" and RQ2: "What is the impact of the usage of a data-driven approach and ML on perishable food waste optimisation?". This research implemented the following inclusion criteria: (1) published between 2015-2024. The selection of this date range is based on contemporary academic articles and reflects the most up-to-date research findings in the field; (2) focused on perishable food waste in retail supermarkets and utilised data-driven and machine learning as a solution for food waste optimisation; and (3) peer-reviewed.

Screening and Eligibility Assessment for Data Analysis

Following each search in above mentioned databases, the initial articles were exported into Zotero. After removing the duplicates, all titles and abstracts were screened to select the relevant articles based on the inclusion criteria and to ensure relevance according to research questions. The selection of articles was checked and categorised into included and excluded studies after the initial screening. The full text of the included category was then assessed against the inclusion criteria. A flow chart of the research selection procedure is presented in Figure 1.

Figure 1: Flow Chart Depicting the Process of Article Selection for the Systematic Literature Review



Note: Search Key words were (food waste prevention) AND (food waste reduction) AND (grocery retail sector) OR supermarket AND (machine learning) AND data-driven AND (demand forecast model) AND (predictive analysis) AND (decision-making for managers).

RESULTS AND DISCUSSION

The description of the results provides the findings of a synthesised evaluation of the 45 selected articles to answer the research questions. Detailed information of these studies is presented in Table 1. Based on the initial results, the articles are mapped according (RQ 1) What are the challenges faced by retail supermarket on perishable food wastage production? and (RQ 2) What is impact of the usage of data-driven approach and ML on perishable food waste optimisation? Articles that did not examine these two RQs were excluded, resulting in 30 articles being selected from 898 results on Google Scholar and ProQuest.

Table 1: Mapping results of the 40 Selected Articles Based on Links to the Research Questions

NUMBER	AUTHORS	RELEVANCE TO THE RQ
1.	Achamu et al., (2021)	RQ 2
2.	Alawadh & Barnawi (2024)	RQ 2
3.	Alfian et al., (2023)	RQ 2
4.	Andaur et al., (2021)	RQ 2
5.	Birkmaier et al., (2024)	RQ 2
6.	Bojer et al., (2019)	RQ 2
7.	Cicatiello et al., (2020)	RQ 1
8.	Dibsi & Cho (2023)	RQ 2
9.	Fredes et al,. (2023)	RQ 1
10.	Goodman-Smith et al., (2020)	RQ 1
11.	Haselbeck et al., (2022)	RQ 2
12.	Horoś & Ruppenthal (2021)	RQ 1
13.	Joensuu et al., (2022)	RQ 1
14.	Kayikci et al., (2022)	RQ 1 and 2
15.	Kerzel (2022)	RQ 2
16.	Kirci et al., (2022)	RQ 1
17.	Luo et al., (2021)	RQ 1
18.	Marques et al., (2021)	RQ 1
19.	Mattsson & Williams (2022)	RQ 1
20.	Miguéis et al., (2022)	RQ 2
21.	Mitra et al., (2022)	RQ 2
22.	Nasseri et al., (2023)	RQ 2
23.	Nasteski (2017)	RQ 2
24.	Ping et al., (2024)	RQ 2
25.	Riesenegger & Hübner (2022)	RQ 2
26.	Rodrigues et al., (2024)	RQ 2
27.	Sakoda et al., (2019)	RQ 1 and 2
28.	Sarker (2021)	RQ 2
29.	Scholz & Kulko (2022)	RQ 2
30.	Zhang & Yan (2024)	RQ 2

The Challenges of Perishable Food Waste in Retail Supermarkets

Retail supermarkets are reported as one of the sectors that contributed to the production of food waste (Joensuu et al., 2022). In dealing with food waste reduction, it is important to look at the solution according to the hierarchy in which preventing food waste is considered as a desirable solution (Joensuu et al., 2022). From all the types of food waste from retail supermarkets, research reported that fresh vegetables and fruit are mostly being discarded due to their apparent imperfections and oversupply (Fredes et al., 2023; Goodman-Smith et al., 2020; Joensuu et al., 2022; Smith et al., 2020). Unfortunately, retail supermarkets mostly use food donations in addition to sending their food waste to the landfill (Goodman-Smith et al., 2020). According to Goodman-Smith et al., (2020), not all retail supermarkets have the option to donate food to food rescue organisations, and they will not accept all available donations due to capacity reasons.

This limitation highlights the need to focus on food waste prevention at its source. By minimising food waste, the demand of food redistribution would decrease, in addition, reducing food waste at the source being more effective than relying on food donations (Goodman-Smith et al., 2020).

Prevention ought to be considered first when it comes to preventing food waste. Understanding the root causes of in-retail supermarket food waste is essential before implementing food waste prevention strategies (Cicatiello et al., 2020). One of the causes highlighted is overstocking due to inaccurate prediction of fresh food demand (Cicatiello et al., 2020). Based on a survey conducted by Fredes et al. (2023), overstocking is associated with retail supermarket planning, over buying, and purchasing without a sales plan, all of which will contribute to unavoidable food waste. It is reported that citrus, banana, inflorescence (broccoli, cauliflower, artichoke), and root and tubers (carrot, beet, turnip, parsnip) food waste are caused by poor retail supermarket planning and purchasing (Fredes et al., 2023). Poor retail supermarket planning correlates with the difficulties to provide accurate demand prediction and forecasting due to seasonal demand, promotion, and weather which lead to surplus food and food waste especially for the fresh food category (Horoś & Ruppenthal, 2021; Kirci et al., 2022). Meanwhile, research identified that some of the retail supermarkets were over-buying by more than 7% to ensure that the shelves were full, which is a driver of customer satisfaction (Goodman-Smith et al., 2020). Horoś and Ruppenthal (2021) discovered through interview with retail supermarket owners that overstocking levels are approximately 30%, largely attributed to customer expectation of constant product availability. These customer behaviours have forced the retail supermarkets to overstock to increase the retail supermarket image and brand loyalty even though it has an impact to the production of food waste (Marques et al., 2021).

Planning systems are important as a food waste prevention strategy of fresh food products in retail supermarkets. By looking at the inventory stocks and sales, retail supermarkets can estimate future orders and find ways to avoid overstocking while meeting customer expectations of product quality and availability (Horoś & Ruppenthal, 2021; Sakoda et al., 2019). This also enables the retail supermarkets to prepare for food loss and waste (FLW) which involves demand management where inaccurate forecasting is one of the causes of food waste (Luo et al., 2021). It is important for the retail supermarket managers to place accurate orders for fresh food which will help to control the amount of food waste generated. They also need to consider the inventory stock balance both in the inventory system and the warehouse. In addition, paying attention to campaigns, weather forecasts, public holidays, and events have a significant effect in predicting customer demand to reduce the amount of perishable food waste (Mattsson & Williams, 2022).

Data-Driven and Machine Learning for Perishable Food Waste Optimisation

For retail supermarkets, monitoring sales, orders, and inventory levels is essential for demand forecasting and predictive analysis, particularly when dealing with short-shelf-life products that risk being discarded if unsold (Haselbeck et al., 2022). This also aims to avoid overstocking and out-of-stock circumstances (Haselbeck et al., 2022). Sustaining retail supermarket operations through sufficient stock levels is the goal of an efficient inventory management system (Praveen et al., 2020). Algorithms powered by ML can be used to optimise perishable items (Achamu et al., 2021). Simply explained, ML is the capacity of a machine to process large amounts of data and is a computing system that gets better with practice. Less errors and greater accuracy are the results of ML in predictive modelling (Achamu et al., 2021). To reduce food waste and boost operational effectiveness, research by Kumar et al., (2021) emphasised the significance of effective inventory management in warehouses by utilising ML for predictive analysis of customers' demand. The ML and data-driven approaches also enable the retail supermarkets to detect out-of-stock (OOS) items automatically using the Point-of-Sale (POS) data and learning algorithms such as Random Forest and Ensemble Classifier to improve the predictive analysis (Kumar et al., 2021). With accuracy of 72%, this algorithm helps the retail supermarkets to control the inventory of perishable products (Andaur et al., 2021).

According to Riesenegger and Hübner (2022), demand forecasting for perishable food products in retail supermarkets is essential because of frequent reordering and fluctuating customer perceptions of products' freshness. When using a data-driven approach for ML-based forecasting, information on inventory levels, demand trends, and other relevant variables must be gathered and analysed (Dibsi & Cho, 2023). Data-driven models can produce precise demand forecasts for perishable food products by utilising relevant data such as previous POS data, trends, and external factors, i.e., weather and public holiday information resulted in increasing profit, improving product freshness and eliminating perishable food waste (Dibsi & Cho, 2023; Haselbeck et al., 2022; Kumar et al., 2021; Riesenegger & Hübner, 2022). Temperature variations influence customer behaviour and product demand, therefore integrating weather data improves forecasting accuracy (Riesenegger & Hübner, 2022). Additionally, in the retail supermarket stage of the perishable food supply chain, a data-driven approach supports the dynamic pricing strategy to determining pricing at various points during a sales season (Kayikci et al., 2022). Dynamic pricing strategy has resulted in 27% of deli and prepared food categories and 53.6% of produce category food waste reduction with a 10% increase in revenue (Sakoda et al., 2019; Scholz & Kulko, 2022). As a result, retail supermarket managers can effectively make quick decisions about the inventory whereby the dynamic pricing is updated based on real-time data of the perishable food shelf-life (Kayikci et al., 2022; Ping et al., 2024). Moreover, it is anticipated that the forecasting tool will include supply synchronisation with perishable food producers in order to lower supply chain aging and raise the in-retail supermarket's product quality (Birkmaier et al., 2024).

Meanwhile, according to Makridakis and Hyndman (1997), and Arunraj et al, (2016), it was stated that there are two types of factors that affect demand prediction: internal factors such as marketing campaigns, price variations and promotions; and external factors, such as weather, festivals, and events in which both factors are uncontrollable. Moreover, customer's behavioural data is also important as an influencing variable in developing the prediction models ML using neural networks (Alawadh & Barnawi, 2024). As an example, according to Kerzel's (2022) analysis, it was found that deli and prepared food categories had the most frequent and short 'days between visits' which means customers tend to buy the food for immediate consumption compared to the milk product category. Therefore, POS data plays an important role in gaining insight of customer purchasing behaviour.

A data-driven approach will be more effective if it is combined with ML algorithm. With a major focus on fruit and vegetables, ML is mostly used in demand forecasting for perishable food products in retail supermarkets. Studies conducted by Priyadarshi et al. (2019) and Arunraj et al. (2016) reported that the ML trend is used in forecasting the daily demand of tomatoes, onions, potatoes, and bananas using ML models such as Long Short-Term Memory (LSTM) networks, Support Vector Regression (SVR), Random Forest Regressions (RF), etc. These models are designed to estimate consumer demand for fresh products with enough accuracy to optimise inventory management and minimise waste (Priyadarshi et al., 2019 & Arunraj et al., 2016). On the other hand, the fish production model makes use of neural network approaches (Miguéis et al., 2022). Therefore, once ML-based predictive analysis has gone through data-driven modelling and training using a well-suited learning algorithm, the model is tested to check it can generate accurate predictions (Sarker, 2021). Further research mentioned that a supervised ML model using Logistic Regression, K-Nearest Neighbour, Decision Tree, Random Forest, etc enable the evaluation of customer purchasing behaviour (Alfian et al., 2023; Bojer et al., 2019; Nasteski, 2017). Mitra et al., (2022) stated that the XGBoost model of learning algorithm provides precise demand forecasting and reduces errors by training the decision trees, therefore, it overcomes the overfitting problem on ML learning algorithm. XGBoost is known for its efficiency and high performance in purchase probabilities prediction in which it is suitable to reduce overstocking of perishable food and optimise its waste production (Nasseri et al., 2023). Integrating Autoregressive Integrated Moving Average (ARIMA), Long Short-Term Memory (LSTM), and Frequent Pattern (FP)-Growth algorithms have also enabled the retail supermarkets to obtain accurate sales forecasting, restocking optimisation, and pricing adjustment leading to waste reduction and operation efficiency (Ping et al., 2024). According to Rodrigues et al. (2024), Random Forest and LSTM neural network algorithms forecasting model achieve the most effective results in reducing food waste, with reductions ranging between 14-52%. Meanwhile, individual item data processing using ARIMA model analyses which fresh food product has the largest purchase amount, catchweight quantity, and sales volume, making it the most profitable item in its category (Zhang & Yan, 2024). As a result, retail supermarket managers and buyers will be better equipped to navigate the challenges of managing perishable food waste, which will improve operational outcomes, keep high profit, and increase customer satisfaction. They will also gain insight into product popularity, product level promotion demand, and customer interest (Alfian et al., 2023; Bojer et al., 2019; Ping et al., 2024; Sakoda et al., 2019).

Combining the first and second research question, this research emphasises that fresh food items are important for retail supermarkets, accounting for up to 40% of their revenue (Felix, 2018). Reducing perishable food waste is therefore essential to improve profitability (Felix, 2018). Tesco, a large retail supermarket in the United Kingdom, is a success story in this regard (Kolev et al., 2023). Tesco has started to implement ML algorithms to optimise their food waste (Kolev et al., 2023). Tesco faces the challenge of managing the food stock leading to revenue loss and increase in food waste (Kolev et al., 2023). In addressing this issue, the supermarket uses ML models with domain expertise that helps in selecting relevant features, interpreting results accurately, and related to the business objective which is increasing revenue while reducing perishable food waste. This algorithm has had the biggest impact on fresh food items. Tesco has cut the number of expiring fresh foods going to waste by 5%, saving millions of fresh products each year (Kolev et al., 2023). Moreover, implementing an advanced demand forecasting system saved Tesco up to £100 million annually (Felix, 2018). In addition, Tesco utilises ML algorithms to reduce food waste by improving forecasting and stock management (Tesco, 2024). Using the supermarket's data, Tesco matches the right product ranges and sizes to their supermarket store size (Tesco, 2024).

CONCLUSION

In achieving SDG 12, Responsible Consumption and Production, this article identified the challenges of perishable food waste reduction in retail supermarkets and examined the usage of data-driven and machine learning approaches as food waste optimisation in the prevention stage. Through a systematic literature review conducted from 30 articles, the findings revealed that retail supermarkets have complex problems with perishable food waste that call for comprehensive solutions. The main causes of the problem are overstocking, imprecise demand prediction, and customer buying behaviour wanting perfect product appearance (Cicatiello et al., 2020; Kayikci et al., 2022; Riesenegger & Hübner, 2022). Despite recognising prevention as the best solution, retail supermarkets frequently turn to unsustainable methods such as food donation and landfill disposal (Riesenegger & Hübner, 2022). This highlights the urgent need for the implementation of better food waste management. Moreover, this research highlights the urgency of the food waste prevention stage by utilising data-driven and ML approaches for predicting accurate demand. For running data-driven and ML modelling, large relevant volumes of data such as sales trends, inventory levels, and external factors as parameters is needed (Dibsi & Cho, 2023;

Haselbeck et al., 2022; Kumar et al., 2021; Miguéis et al., 2022; Riesenegger & Hübner, 2022). Meanwhile, ML also enables dynamic pricing strategy which helps the retail supermarkets to decrease food waste while increasing their revenue (Kayikci et al., 2022; Ping et al., 2024; Sakoda et al., 2019; Scholz & Kulko, 2022). Moreover, accurate forecasting is provided by ML models such as Random Forest and XGBoost, which reduce food waste production and overstocking (Mitra et al., 2022; Nasseri et al., 2023). Overall, retail supermarkets are better equipped to handle the challenges of perishable food waste when data-driven and ML algorithms approaches are combined. This promotes a more resilient and sustainable retail ecosystem by lowering food waste while also improving operational outcomes, profitability, and customer satisfaction.

However, this research acknowledges potential limitations. The selection of the search keywords may have limited the research even though the authors believe the appropriate terms were selected. Furthermore, the article selection process can be viewed as subjective, and the findings might be biased. Therefore, further research is needed to explore the effectiveness of data-driven approach and ML for retail supermarkets in New Zealand in the prevention stage of reducing food waste.

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