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Food Waste Prevention Options in Grocery Retail

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List of Abbreviations

CD	Cross-dock delivery
CPG	Consumer packaged goods
DC	Discounter
DSD	Direct store delivery
ED	Expiration date
$FEFO$	First-expire-first-out
FTL	Full-truckload
$GTIN$	Global trade item number
HLM	Hierarchical linear modeling
$HGLM$	Hierarchical generalized linear modeling
HM	Hypermarket
$LEFO$	Last-expire-first-out
LTL	Less-than-truckload

OS	Organic store
P	Proposition
RQ	Research question
SC	Supply chain
SDG	Sustainable development goal
SE	Standard error
SKU	Stock keeping unit
SM	Supermarket
$SSCC$	Serial shipping container code
$UCPED$	Undesirable customer picking for expiration dates
$WRCP$	Waste ratio customer picking
WS	Wholesaler

1 Introduction

This doctoral thesis explores options for food waste prevention in grocery retail. It presents a structured approach for retailers to mitigate waste in their operations, reveals the customer behavior of picking for expiration dates (EDs) as a substantial root cause for retail food waste, and develops options for proactive mitigation of customer picking within the scope of retail operations.

In this first chapter, this thesis is motivated by the challenge of food waste in Section 1.1. Section 1.2 then defines the scope and outlines the relationship of the three contributions (papers) in regard to food waste prevention in grocery retail.

The remainder is structured as follows. Chapter 2 gives an overview of the three papers forming the core of this dissertation. Information on contributing authors and publication status is provided before each paper is summarized by outlining the purpose, methodology, and findings. The three full-length papers can be found in Chapter 3 to Chapter 5. Finally, Chapter 6 concludes this thesis by synthesizing the findings and outlining areas of future research.

1.1 The challenge of food waste

The Sustainable Development Goals (SDGs) established in 2015 by the United Nations address various social, economic, and environmental challenges. Target 12.3 of the SDGs is to "halve per capita global food waste at the retail and consumer levels and reduce food losses along production and supply chains, including post-harvest losses by 2030" (United Nations, 2015). However, with less than half of the time remaining, food waste still occurs at alarming rates globally (United Nations, 2023). Food waste has social, economic, and environmental aspects that must be considered.

First, food waste is a social issue. With more than one in nine people worldwide suffering from malnutrition and hunger, food insecurity remains a critical challenge (World Food Programme, 2023). Notably, reducing waste in supply chains by just 50% in high-income countries could potentially alleviate hunger for up to 63 million people in low-income nations (Munesue et al., 2015). Further, the cost of food waste is a significant financial burden. In the European Union alone, 59 million tonnes of food waste are generated with related costs of EUR 132 billion per year (Eurostat, 2020). Thus, the amount of food wasted surpasses the total volume of food imports (Feedback EU, 2022). Lastly, the production and distribution of food are energy-intensive, occupy land, and utilize freshwater resources. Thus, wasting food also means wasting resources (Akkaş and Gaur, 2022). Global food loss and waste significantly contribute to greenhouse gas emissions, accounting for approximately 8-10% of the world's total emissions. Taken as a country, food waste would be the third-largest emitter globally, only behind China and the United States (Food and Agriculture Organization, 2020).

These numbers underscore the urgent need for efforts to address food waste as a critical component of global food security, social justice, and climate change. The scope of this thesis in the context of food waste mitigation will be detailed in the following.

1.2 Food waste prevention in grocery retail

Food waste occurs throughout the entire food supply chain, from the farms to consumers. The Environmental Protection Agency (2019) developed a general food recovery hierarchy that prioritizes actions to reduce food waste. The six levels visualized in Figure 1.1 range from source reduction as the most preferred option to landfill as a last resort. This thesis focuses on level one of the hierarchy. Preventing surplus of food before it emerges is the most social, economic, and ecological option to tackle food waste. Further, within the supply chain, this thesis is dedicated to the retail stage. Retail plays a pivotal role in food waste prevention as it connects supply and demand, and decisions taken at the retail stage influence upstream processes and downstream customer behavior.

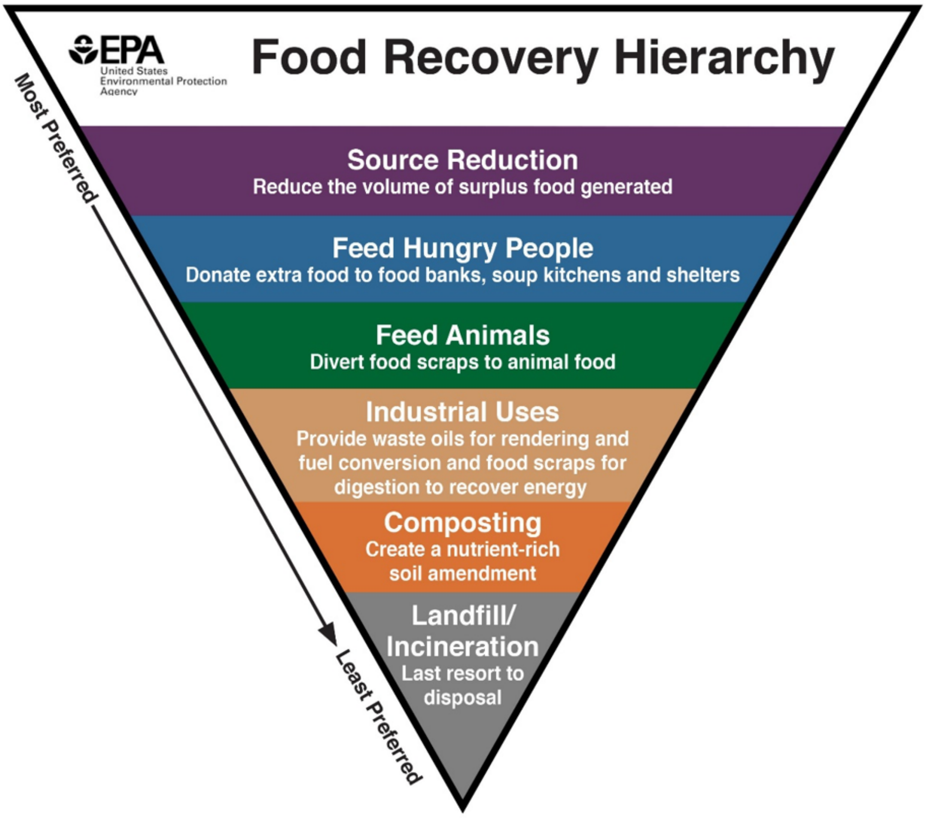


Figure 1.1: Environmental Protection Agency (2019): Food recovery hierarchy

Besides the social and ecological aspects, reducing food waste is a business case for retailers. In European grocery retailing, food waste costs typically average between 1-2% of gross sales (Klingler et al., 2016). With net profit margins ranging around 3% (McKinsey, 2023), retailers could drastically boost their profit margins by preventing food waste. Further, managing food waste also helps retailers manage risks. With the growing awareness of the food waste challenge, policy regulations and reputation issues may further increase the costs associated with food waste in the future (Akkaş and Gaur, 2022). Therefore, identifying food waste drivers and implementing effective waste management strategies has become imperative for retailers.

However, grocery retailers are in a dilemma. Faced with fierce competition and rising customer expectations related to high product variety and high availability, they tend to increase assortments and overstock their shelves (see, e.g., Kök et al., 2015; Broekmeulen and van Donselaar, 2016). This dynamic leads to a delicate trade-off where retailers have to balance between satisfying customer expectations and the risk of overstocks that convert into food waste. Resolving this trade-off is particularly challenging for perishable and highly perishable products with shelf lives of a few weeks or even just a few days upon arrival at the store. This requires efficient inventory management to minimize the risk of stock-outs and wastage at the same time. While the culture in the retail industry has long accepted food waste as an investment, it is now changing towards a more sustainable approach (Akkaş and Gaur, 2022).

In this dissertation, options for food waste prevention in grocery retail are explored. Figure 1.2 visualizes the relationship of the three papers composing the main body of the thesis. Given the exploratory nature of this research endeavor and the complexity of retail operations, this thesis requires various research methodologies. Both qualitative and quantitative approaches are applied to explore this nascent research field. A concise overview of the three papers and the chosen methodological approach is outlined in the following.

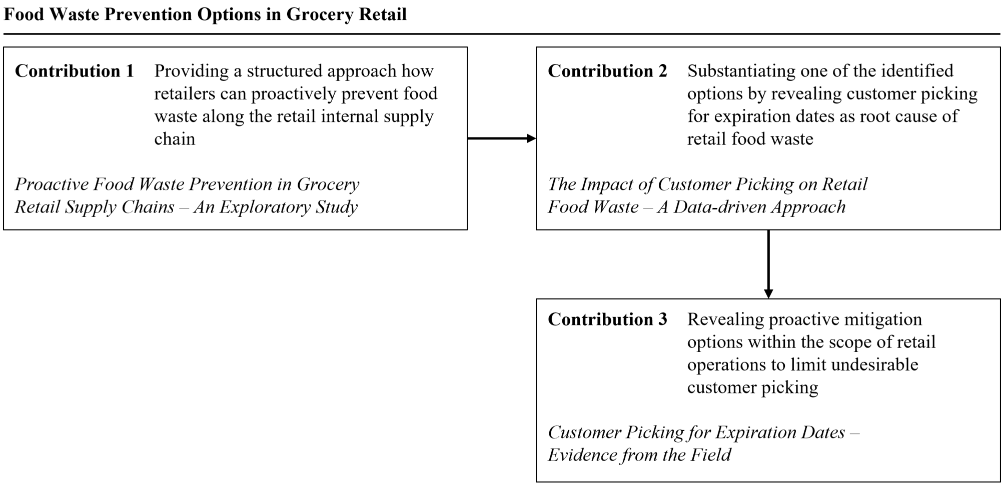


Figure 1.2: Relationship of the three papers

Paper 1 (see Chapter 3) introduces the differentiation between reactive reduction and proactive prevention options along the retail internal supply chain. Comprising options from inbound logistics to the store, it provides a structured approach to how retailers can proactively prevent food waste before a surplus emerges. The conceptualization of food waste prevention options and implementation patterns is of utmost importance for retailers willing to tackle food waste. As food waste prevention in retail is still a nascent topic, an exploratory approach based on qualitative interviews with retail experts is adopted. For data analysis, an interpretive research methodology comprising two layers is applied. First, a content analysis is conducted to identify waste mitigation options, barriers, and impacts. Second, for conceptual theory building, a subjective analysis reveals the rationales and effects behind the identified options.

One highly impactful and widely applied option revealed in Paper 1 is shelf merchandising, i.e., executing a strict first-expire-first-out (FEFO) shelf arrangement. Paper 2 (see Chapter 4) builds on these findings and substantiates customer picking for EDs as a root cause for retail food waste. Developing a novel method to estimate food waste caused by customer picking when ED information on batch level is available builds the empirical foundation. This is particularly important as it reveals associated food waste costs of the customer picking behavior and allows retailers to conduct a profound cost/benefit analysis. To close the existing information gap, cooperation with a retail partner and collection of field data was necessary. Within a nine-month data collection period, ED data was recorded to gain ED visibility for all batches shipped from the warehouse to the stores. The proprietary data set is analyzed in two steps. First, analytical modeling is required to classify waste caused by customer picking in panel data. Second, the resulting cross-sectional data set is analyzed with various regression models to reveal store and product-related drivers.

Finally, Paper 3 (see Chapter 5) moves towards quantifying and mitigating customer picking. An empirical foundation of customer picking is imperative as a growing body of analytical and modeling literature lacks an empirical justification for customer withdrawal behavior. Identifying the interrelationships between customer picking and options in shelf design and replenishment is the foundation for deriving proactive mitigation options and preventing food waste in the future. Similar to Paper 2, data collection in the field was required to investigate undesirable customer picking. However, this time, a series of manual physical data collections were designed and executed to not only observe the effects of undesirable customer picking but actually quantify it. Analytical modeling is required to derive customer picking based on inventory composition data. To derive options for proactive mitigation of customer picking, hierarchical generalized linear modeling is applied to account for the multilevel data structure.

2 Contributions

This chapter provides an overview of the three papers forming this doctoral thesis's core. First, Table 2.1 presents information about the co-authors and the current publication status. Next, following the taxonomy introduced by Brand et al. (2015), Table 2.2 highlights the co-authors contributor roles. Lastly, each of the three papers is summarized, including its purpose, methodology, and findings (see Sections 2.1-2.3).

Paper		Co-authors	Status
1	Proactive Food Waste Prevention in Grocery Retail Supply Chains – An Exploratory Study	Manuel Ostermeier and Alexander Hübner	Accepted and published online in the International Journal of Physical Distribution & Logistics Management (forthcoming)
2	The Impact of Customer Picking on Retail Food Waste – A Data-driven Approach	Fabian Schäfer, Kai Hoberg and Alexander Hübner	Presented at INFORMS MSOM 2023 conference; In the process of submission as of 25.10.2023
3	Customer Picking for Expiration Dates – Evidence from the Field	Fabian Schäfer, Manuel Ostermeier and Alexander Hübner	Presented at INFORMS MSOM 2022 conference; In the process of submission as of 25.10.2023

Table 2.1: Status of publication

Paper & Co-authors		Contributor roles
1	Winkler, Tobias	Conceptualization, Methodology, Validation, Investigation, Data Curation, Writing - Original Draft, Visualization, Project administration
	Ostermeier, Manuel	Conceptualization, Validation, Writing - Review & Editing, Supervision
	Hübner, Alexander	Conceptualization, Methodology, Validation, Writing - Original Draft, Writing - Review & Editing, Project administration, Supervision
2	Schäfer, Fabian	Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Resources, Writing - Original Draft, Writing - Review & Editing, Project administration
	Winkler, Tobias	Conceptualization, Methodology, Formal analysis, Investigation, Writing - Original Draft, Visualization
	Hoberg, Kai	Conceptualization, Methodology, Writing - Review & Editing, Supervision
	Hübner, Alexander	Conceptualization, Methodology, Writing - Review & Editing, Supervision
3	Winkler, Tobias	Conceptualization, Methodology, Formal analysis, Investigation, Data Curation, Writing - Original Draft, Visualization, Project administration
	Schäfer, Fabian	Conceptualization, Methodology, Validation, Formal analysis, Investigation, Writing - Original Draft, Writing - Review & Editing, Supervision
	Ostermeier, Manuel	Conceptualization, Validation, Writing - Review & Editing, Supervision
	Hübner, Alexander	Conceptualization, Methodology, Validation, Writing - Original Draft, Writing - Review & Editing, Project administration, Supervision

Table 2.2: Contributor roles following the taxonomy of Brand et al. (2015)

Remark The papers submitted to the journals may have slight variations to the versions of Chapter 3 to Chapter 5. The reasons are journal-specific formatting guidelines and modifications made during the peer review process. Nonetheless, the fundamental relevance and contributions of the papers persist.

2.1 Proactive Food Waste Prevention in Grocery Retail Supply Chains – An Exploratory Study

Purpose Due to the economic, social, and ecological implications of food waste, the identification of the drivers of waste and its management has become a top priority of retailers. Predominant strategies identified in current retail practice are reactive options at the store level, e.g., price discounts, donations, or disposal. Those options mitigate the consequences of surplus but do not tackle its causes. Therefore, this paper aims to identify options for retailers to proactively prevent food surplus before it emerges and analyze the *"how"* and *"why"* of food waste prevention.

Methodology Food waste prevention in retail is still a nascent topic. Hence, an exploratory approach is applied to obtain insights into measures taken in practice. Interviews with practitioners responsible for food waste prevention from different contexts in grocery retail build the main data source. An interpretive research approach is adopted, and interview outcomes are analyzed in two layers. The first layer comprises a content analysis to identify waste mitigation options, barriers, and impacts. Subsequently, a subjective analysis focusing on the rationales and effects behind the identified options is carried out. The internal and external validity of the findings is ensured by employing rigorous data collection methods, maintaining transparency in the research process, triangulation with different data sources, and confirmation checks with the interview partners.

Findings 21 inbound, warehousing, distribution, and store-related options are currently applied in grocery retail to mitigate food waste. While preventing food surplus before it emerges is the most ecologically and economic approach, both retailers and research have been focused on reactive food waste reduction options in stores. Conceptualizing implementation patterns reveals that prevention measures in inbound logistics, distribution & warehousing, and upstream store operations have not been intensively applied to date. The 21 options identified are further aggregated with regard to *"how"* and *"why"* waste is minimized. A novel framework for food waste prevention and reduction options within retail operations and six research propositions for food waste prevention are presented. Figure 2.1 provides an overview of the findings.

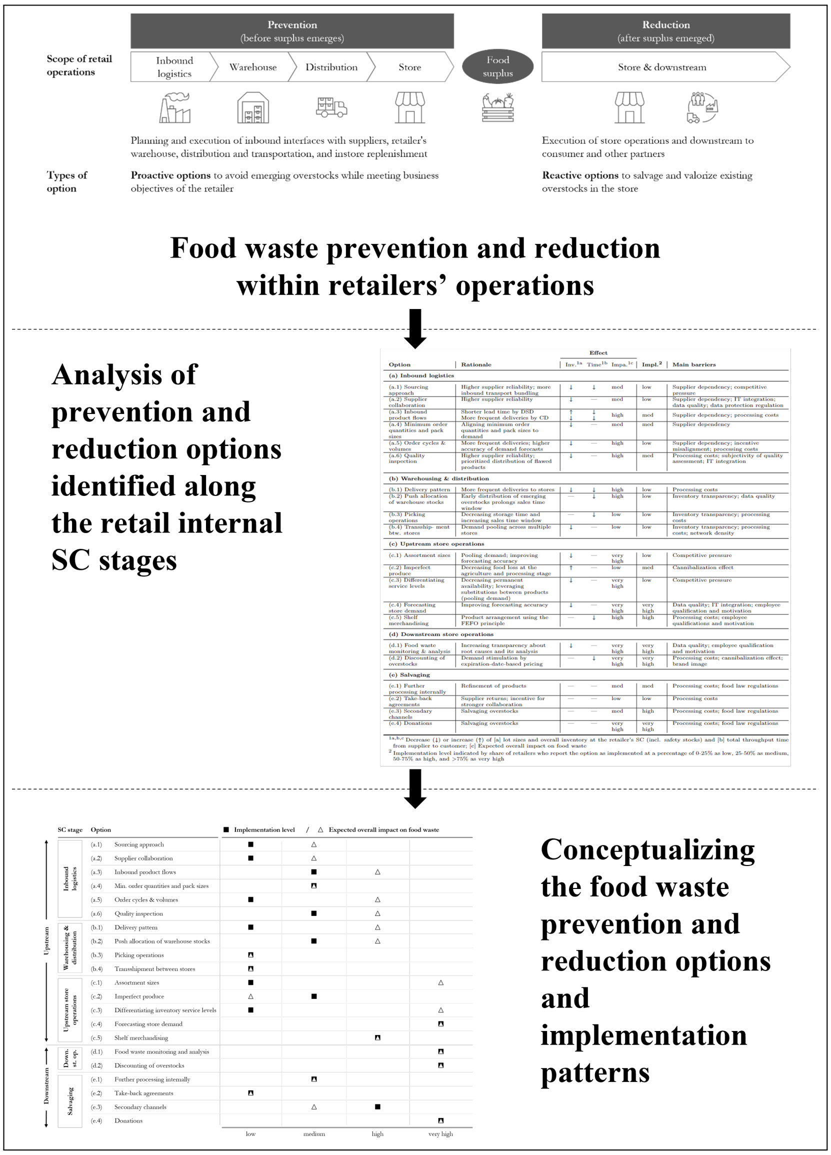


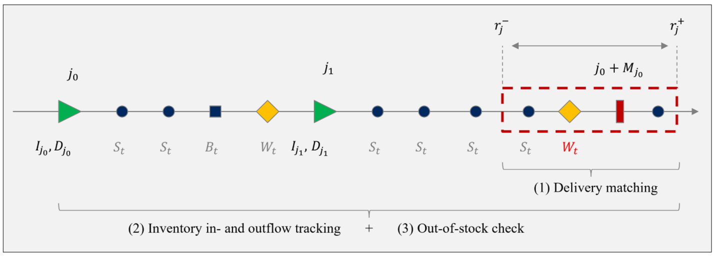
Figure 2.1: Poster summary for Contribution 1

2.2 The Impact of Customer Picking on Retail Food Waste – A Data-driven Approach

Purpose Retailers rotate their inventories at the store to ensure that products are sold in the order of their impending expiration. Customers, however, may violate the retailer's intended withdrawal sequence and seek fresher products from the back of the shelves. Customer picking for expiration dates is seen as a root cause of retail food waste in research and retail practice. However, the extent to which customer picking causes food waste at the retail stage has not yet been empirically quantified. Therefore, this paper aims to estimate food waste caused by customer picking and reveal store and product-related drivers for this waste.

Methodology Missing data so far impeded attempts to connect customer picking with food waste at the retail stage. In cooperation with a leading European grocery retailer, a process adaption was implemented at one pilot warehouse, and ED data were collected to overcome the information gap. The gained ED visibility for all batches shipped from the warehouse to the stores builds the foundation to quantify the food waste caused by customer picking. Based on a proprietary panel data set, a two-step approach for quantification and driver identification is applied. First, a method for customer picking waste identification in panel data is developed, and second, store and product-related drivers of this waste are investigated with various regression models.

Findings Results show that 45% of retail food waste in the chilled assortment is caused by customer picking for EDs in our sample. For three of the four investigated product categories, the customer picking waste ranges between 43% and 49%. Only the Convenience category has lower customer picking waste rates with, on average, 28% (see Figure 2.2). This waste could have been prevented if customers had adhered to the retailer's intended withdrawal sequence. Thus, customer withdrawal behavior is a promising lever for retailers to prevent food waste. Results for the driver identification reveal that products with high turnover rates and short shelf lives are especially prone to customer picking waste and should receive more attention in retail practice. Further, retailers can mitigate customer picking waste by limiting the ED variety on the shelf and by applying ED-based pricing for soon-to-expire products.



Method for customer picking waste identification

Product category	Mean food waste ratio	Mean customer picking waste ratio
Cheese	3.6%	47%
Convenience	5.5%	28%
Delicacies	7.1%	43%
Milk/Dairy	4.7%	49%
Total	**5.5%**	**45%**

45% of retail food waste is caused by customer picking for expiration dates

Variables	Cheese	Convenience	Delicacies	Milk/Dairy	**All**
(Intercept)	0.358***	0.366***	0.243***	0.299***	**0.290*****
WeeklySales	0.108***	0.108***	0.114***	0.111***	**0.110*****
RSL	-0.005***	-0.005***	-0.002***	-0.005***	**-0.004*****
EDVariety	0.074***	0.047***	0.062***	0.047***	**0.061*****
EDPricing	-0.191***	-0.321***	-0.145***	-0.287***	**-0.209*****
RetailPrice	0.006	0.004	0.023***	0.047***	**0.027*****
Organic	0.013	-0.005	0.013	0.026***	**0.024*****
Controls	✓	✓	✓	✓	✓
R^2	0.176	0.147	0.166	0.154	**0.172**
$Adj.R^2$	0.175	0.146	0.166	0.154	**0.172**
Observations	13,968	7,926	44,835	67,182	**133,911**

*p<0.05; **p<0.01; ***p<0.001

Customer picking waste driver identification

Figure 2.2: Poster summary for Contribution 2

2.3 Customer Picking for Expiration Dates – Evidence from the Field

Purpose Customer picking for EDs in grocery retail leads to disorder on shelves, damaged products, and leaves soon-to-expire products on the shelves. Therefore, it is recognized as a root cause of food waste at the retail stage. To support retailers in preventing food waste, an empirical foundation for decision-making is required. Hence, the goal of this paper is to quantify the extent of customer picking and to reveal options for proactive mitigation within the scope of retail operations.

Methodology As barcodes and, thus, scanner data do not contain ED information, manual data collection is required to investigate undesirable customer picking. A series of physical data collections were designed and executed in collaboration with a leading European grocery retailer. Based on inventory composition data, customer picking is identified on the delta between two consecutive observations. This unique data set provides transparency on customer choices on an ED level for 42 products (associated with 14 product groups) in six stores. Due to the multilevel structure of the data, hierarchical generalized linear modeling is applied to analyze options for proactively mitigating customer picking.

Findings The average customer picking share observed is 29%, with a lower bound of 26% and an upper bound of 35%. For the majority of the product groups investigated (10 out of 14 groups), the rate ranges between 22% and 33%. Furthermore, options in store operations that can significantly mitigate the undesirable picking are revealed. The first set of options is related to the influence of shelf plans on customer search effort. The effects of the shelf level, the shelf space, and the grabbing space show that customer picking can be mitigated by increasing the ED search effort for customers. Further, customer picking increases with a lower minimum remaining shelf life of the foremost item, which depends on the product and store operations. This highlights the importance of minimizing throughput times from the supplier to the shelf and prioritizing highly perishable products for frequent inventory rotation. Lastly, the ED variety drastically increases customer picking. Hence, besides focusing on availability, retailers should actively manage the amount of different EDs on the shelf. Figure 2.3 provides an overview of the research endeavor.

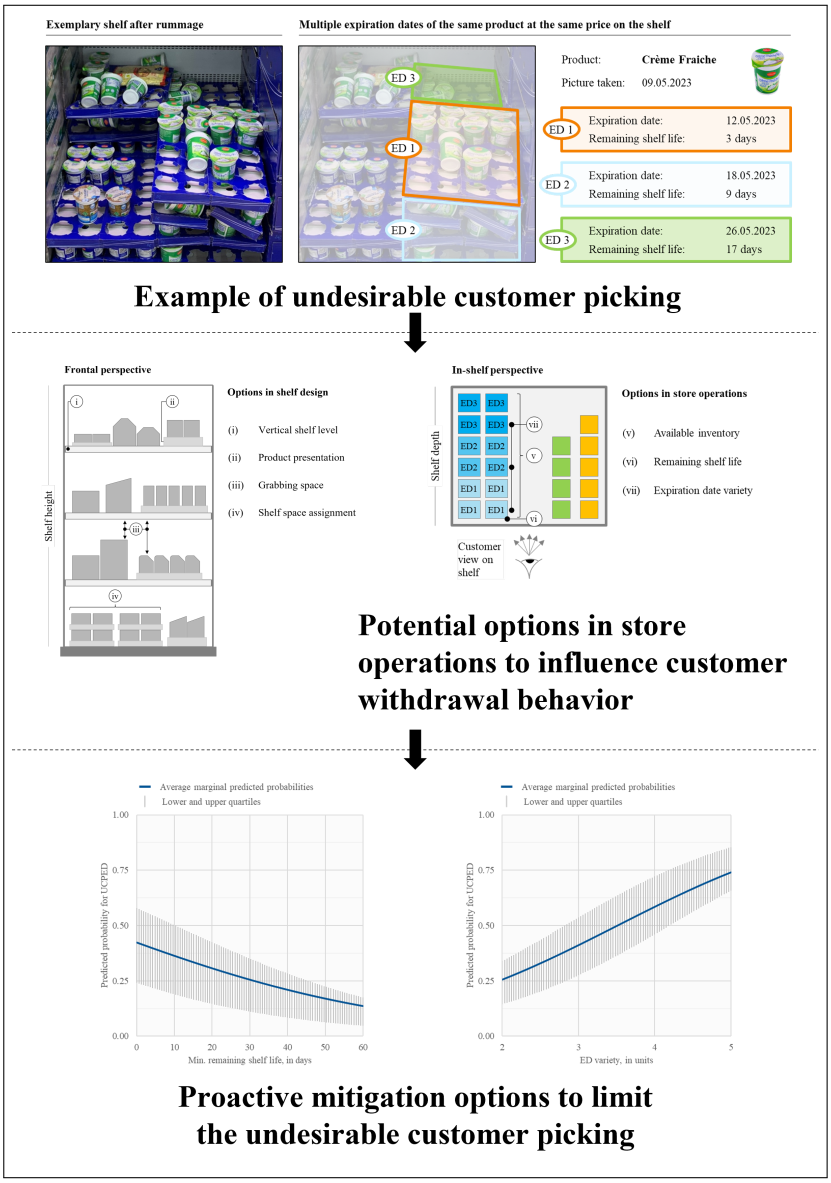


Figure 2.3: Poster summary for Contribution 3

3 Proactive Food Waste Prevention in Grocery Retail Supply Chains – An Exploratory Study

Co-authors: Manuel Ostermeier and Alexander Hübner
Accepted in *International Journal of Physical Distribution & Logistics Management*

Abstract **Design/methodology/approach** – We follow an exploratory approach for a nascent topic to obtain insights into measures taken in practice. Interviews with experts from retail build the main data source.
Purpose – Regarding the retail internal supply chain (SC), both retailers and research are currently focused on reactive food waste reduction options in stores (e.g., discounting or donations). These options reduce waste after a surplus has emerged but do not prevent an emerging surplus in the first place. This paper reveals how retailers can proactively prevent waste along the SC and why the options identified are impactful but, at the same time, often complex to implement.
Findings – We identify and analyze 21 inbound, warehousing, distribution, and store-related options applied in grocery retail. Despite the expected high overall impact on waste, prevention measures in inbound logistics and distribution & warehousing have not been intensively applied to date.
Practical implications – We provide a structured approach for retailers to mitigate waste in their operations and categorize the types of barriers that need to be addressed.
Originality/value – This research provides a better understanding of prevention options in retail operations, which has not yet been empirically explored. Furthermore, it conceptualizes prevention and reduction options and reveals implementation patterns.

3.1 Introduction

Reducing food waste is a grand societal challenge. While more than 10% of the world population still faces hunger, approximately one-third of all food produced is lost or thrown away (FAO, 2021). In addition to the social injustice, food waste induces severe economic and ecological issues, and therefore the United Nations targets halving food waste by 2030 (United Nations, 2015). To achieve this goal, it becomes indispensable to identify and work on options to minimize food waste in grocery retail, which is pivotal for waste occurrence as it connects supply and demand. However, the shift towards ever fresher but highly perishable products as a value proposition and sales opportunity has created a dilemma for grocery retailers. One side of the coin is satisfying customer expectations related to high product variety and high availability, while overstocks that convert into food waste are the other. Huang et al. (2021) screen reports of 199 retailers across 27 countries and identify that eight out of the ten most reported food waste management practices are targeted at reducing existing overstocks and redistributing food surplus. Predominant strategies identified in current retail practice are price discounts, donations or disposal. However, these strategies only represent reactive options at the store level once a food surplus has emerged. It mitigates the consequences of surplus but does not tackle its causes. Following the food waste hierarchy of Papargyropoulou et al. (2014), reduction is only the second best approach. It mitigates the consequences of surplus but does not tackle its causes. The priority is to proactively prevent the overstock before it emerges – from an ecological, social and economic point of view. Figure 3.1 differentiates such reactive reduction and proactive prevention within operations along the retail internal SC from inbound to the store.

The recent report of McKinsey (2022) further emphasizes the importance of prevention. It is estimated that 50-70% of food waste could be saved, highlighting that two-thirds of the savings potential could be realized by preventing food surplus. Prevention requires a comprehensive perspective

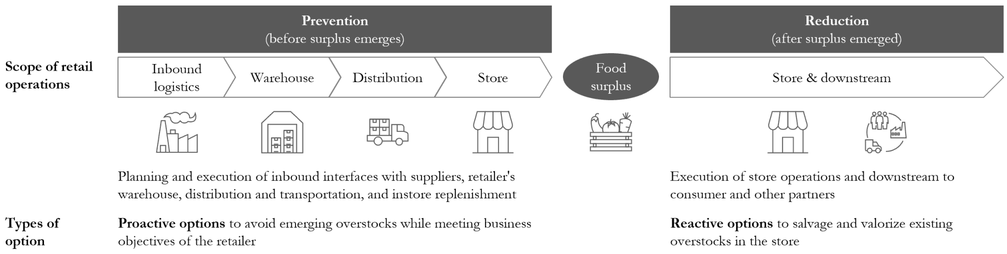


Figure 3.1: Food waste prevention and reduction within retailers' operations

and, in our case, an analysis of the internal retail SC. This includes analyzing store operations and upstream processes that impact inventories and freshness at all stages. These upstream stages – distribution, warehousing and inbound logistics – contribute to food waste prevention as upstream decisions always impact downstream operations at the store (see, e.g., Akkaş et al., 2018; Akkaş and Honhon, 2022). The mutual dependency of the stages makes it necessary to analyze them jointly (see, e.g., Hübner et al., 2013). However, the initial research focus in retail food waste literature has been on its quantification (see, e.g., Parfitt et al., 2010; Lebersorger and Schneider, 2014; Stenmarck et al., 2016), and on causes of waste occurrence (see, e.g., Mena et al., 2011, 2014; Teller et al., 2018; Akkaş et al., 2018), while a key focus is now on food waste reduction in stores (see, e.g., Buisman et al., 2019; Riesenegger and Hübner, 2022). This means that current literature mainly deals with reduction options on the store level (on the right of Figure 3.1), and to a large extent, neglects prevention options along the retail internal SC so far (on the left of Figure 3.1). A comprehensive analysis of prevention options upstream of the retail SC, i.e., considering the internal retail SC as a whole, is lacking. Huang et al. (2021) and Akkaş and Gaur (2022) identify a gap in the current literature in understanding how retail operations may contribute to minimizing food waste. Analyzing the internal retail SC will unlock novel practices and broaden awareness of prevention options.

Our fundamental aim is, therefore, to develop insights into opportunities to not only reduce but, in particular, prevent food waste in the internal retail SC, namely in inbound logistics, warehousing & distribution and store operations. Therefore, we investigate options applied in retail practice and further analyze the *"how"* and *"why"* food waste prevention in retail. As research in this area is scarce, we follow an explorative approach to systematically understand food waste prevention rationales, effects, and barriers to the planning and execution of retail operations. The remainder of our work is structured as follows. Section 3.2 analyzes related literature and concretizes the research questions. The methodology is detailed in Section 3.3. Section 3.4 presents empirical findings on minimizing food waste along the internal SC of grocery retailers. Section 3.5 conceptualizes our findings, and Section 3.6 discusses the managerial and theoretical implications and concludes the study.

3.2 Literature review, research gap and question

This section first reviews the related literature. This then builds the basis to detail the research gap and question. The related empirical literature on food waste minimization can be agglomerated into three areas that will be summarized below. Details of the review approach are summarized in the Appendix.

(i) Store-related food waste management Gruber et al. (2016) interview store managers and emphasize the role of the store in food waste reduction. An increase in the autonomy granted to store managers concerning the adaptation of product offers, store operations, and food donation is intended to reduce waste. Using a similar approach, Filimonau and Gherbin (2017) explore the managerial attitudes to food waste minimization. They further find that while food waste recycling and price reductions are mainstream, food donations are ad-hoc and largely occur at managerial discretion. As in Gruber et al. (2016), store managers demand more flexibility that is limited by corporate policies. To address this impact of flexibility, Horoś and Ruppenthal (2021) interview store owners who have greater autonomy than employed managers. They indicate that owners try harder to avoid food waste than managers. Store owners mention their experience and management style concerning precise planning, accurate ordering, and timely price reductions as important mitigation options. Teller et al. (2018) utilize a process simulation on top of store manager interviews to quantify food waste root causes at a store level. They propose measures at a store, retail, and consumer level and conclude that waste management at a store level is critical but has only a short-term impact as it is prone to only fight symptoms rather than going to the root causes. Measures across retail operations must be systematically investigated to achieve long-term impact. Hermsdorf et al. (2017) extend the scope to food banks and explore the impact and barriers of lowering product quality standards and donation practices. Riesenegger and Hübner (2022) analyze reduction approaches to enhance store operations planning.

(ii) Supplier-related food waste management The second area looks at the supplier interface. Earlier publications quantified food waste causes at this stage (see, e.g., Mena et al., 2014; Rijpkema et al., 2014). Kaipia et al. (2013) is one of the first approaches with respect to prevention options. They study material and information flows, specifically on sharing demand and shelf-life data. They apply an exploratory case study. They show that moving the order penetration point closer to the customer avoids waste, which, however, entails better forecasting processes and a balance between make-to-order and make-to-stock, as a larger share of the SC then operates based on forecasts. Liljestrand (2017) build on Kaipia et al. (2013) and extend the scope by focusing on the logistical solutions for reducing waste before it enters the retail SC.

(iii) General reviews on retailers' food waste management De Moraes et al. (2020) review food waste literature and connect causes and retail practices along different categories. Important causes are related to insufficient internal procedures, lacking collaboration with suppliers, inefficient demand forecasting, and a lack of consensus in waste measurement. Reduction rather than prevention options are at the center of the review. The majority of improvement practices deal with procedures and work methods related to collaboration and donation. The authors conclude that different agents in SCs may be involved, and a more systemic view is required. Huang et al. (2021) base their findings on a review of industry reports. By counting retailers that report a practice, they show that redistributing through partnerships, offering imperfect produce, and dynamic pricing are the predominant practices. Akkaş and Gaur (2022) develop a research agenda to reduce food waste with technology, logistics, incentives and coordination, innovation, and behavioral operations. They document an overall lack of insight into prevention.

Research gap and question While deriving insights for better store execution, the scope of the contributions in the area (i) focuses on managers' behavior and their reactive options. Store managers have, however, only a limited decision scope as they need to rely on decisions made upstream of the SC. Studies in the area (ii) show that an SC perspective is essential despite limitations to the supplier-retail interface. The findings further indicate that the logistics solutions are interlinked. Finally, the reviews in area (iii) connect causes and countermeasures for specific areas and focus on reduction. An analysis of the interrelationships to prevent food waste with a more comprehensive perspective on retail operations is lacking, although many aspects of the SC subsystems in inbound, warehousing, distribution, and store operations are interdependent (e.g., inventory management and delivery frequency). To summarize, retail practice and literature put the reduction of food surplus in stores at the center of their strategies. Insights into systematic prevention within the store and upstream of the retail SC constitute open research areas. Furthermore, none of the contributions analyzes the motivation, cause, and effect of implementing certain prevention options or respective barriers that hinder implementation (see also de Moraes et al., 2020; Huang et al., 2021; Akkaş and Gaur, 2022). This study, therefore, explores the following two associated research questions:

How can grocery retailers proactively prevent food waste along the retail internal supply chain? Why are prevention options expected to be effective?

3.3 Research methodology

We followed an exploratory approach to address this emerging research field and obtain first-hand insights into retail practice. Exploratory studies are especially suitable for little-known research areas such as waste prevention in retail operations (Manuj and Pohlen, 2012; Randall and Mello, 2012). Our research follows well-established guidelines for emerging topics from Glaser (1967) and Corbin and Strauss (1990), and relies mainly on expert interviews. We interviewed practitioners responsible for food waste prevention from different contexts in grocery retail. Expert interviews are a suitable instrument for data collection as the knowledge of the experts interviewed stems from their position within the companies (see, e.g., Flynn et al., 1990; Ellram and Edis, 1996; Creswell, 2003).

Sampling Despite the recent increase in online grocery, traditional retailers with brick-and-mortar stores remain by far the largest segment (Kantar, 2021). Moreover, pure online retailers usually have SCs that are fundamentally different (see, e.g., Galipoglu et al., 2018; Wollenburg et al., 2018). We, therefore, focused on retailers operating brick-and-mortar stores. Another sampling criterion was the selling of perishable food products, which are the main drivers of food waste. Consequently, we considered discounters (DC), supermarkets (SM), hypermarkets (HM), organic stores

(OS), and wholesalers (WS) for our sample. Including retailers with different structures creates a sample that shares internal homogeneity (i.e., companies sharing common characteristics and assortments) and external heterogeneity (i.e., companies operating from different consumer expectations, networks, infrastructure, etc.). The interviewees were self-selected by the retailers as the relevant specialists. As food waste responsibilities rest on different shoulders, we interviewed executives from general, SC, sales, sustainability, and quality management. Our final sample consists of 12 retailers operating in Germany and covers more than 85% of the German grocery retail market. We expect the transferability of our results since our research focuses on general SC aspects, and models found in Germany are representative of other developed markets. Most retailers are multinational companies with stores in European and global markets and international operations. Furthermore, we investigated retail structures with a heterogeneous set of retailers. By following the guidelines of Guba and Lincoln (1989) and Halldórsson and Aastrup (2003), we expect that our findings can be generalized across different markets and contexts within modern grocery retailing.

Interviews The interviews took place over six months (from November 2020 to April 2021) with ongoing data coding and analysis after each interview as recommended by Eisenhardt (1989). We applied theoretical sampling in three steps (Corbin and Strauss, 1990). We started by interviewing one retailer from each format identified. After the first round of 5 interviews, we invited additional retailers not yet included in the first round. Another four retailers agreed to participate from different formats. Since we were still gaining more insights after interview 9, we invited further retailers and were able to conduct three more interviews. After another round of data analysis of interviews 10 to 12, we found no significant changes in coding and categorization during the completion and analysis of this sample. As repeatability was high, certain patterns emerged, and insights gained from the interviews became marginal, we concluded data saturation for this sample (Eisenhardt, 1989). Table 3.1

summarizes the retailers and the interviewees.

ID	Retail format	Sales €[1]	#Stores	Interviewee role(s)
SM01	Supermarket	>10bn	>4k	General Regional Manager
OS01	Organic store	1bn-5bn	0.1k-2k	Store Manager
HM01	Hypermarket	>10bn	0.1k-2k	Head of Supply Chain Management
DC01	Discounter	>10bn	>4k	Division Manager Quality Management, Logistics Manager[2]
WS01	Wholesaler	5bn-10bn	<0.1k	Head of Supply Chain Development
SM02	Supermarket	1bn-5bn	0.1k-2k	Head of Replenishment Innovation
DC02	Discounter	>10bn	>4k	Regional Managing Director, Store Manager[2]
HM02	Hypermarket	5bn-10bn	<0.1k	Head of Sales
OS02	Organic store	<1bn	<0.1k	Head of Quality
DC03	Discounter	>10bn	2k-4k	Division Manager Chilled Products
DC04	Discounter	5bn-10bn	2k-4k	Sustainability Manager
SM03	Supermarket	>10bn	2k-4k	Head of Supply Chain Management

[1] Annual sales in Germany in 2021
[2] Two interviews were conducted due to shared responsibilities within the retailer's organization

Table 3.1: Overview of participating companies in chronological order

We applied an interview guide to structuring the discussion (see Table 3.A1 in the Appendix). One pilot interview was conducted. After the pilot interview, minor adaptations were made to the guide allowing the inclusion of the pre-test in the analysis. Interviews were conducted via videoconferencing and lasted 70 minutes on average. Two interviewers with accumulated prior knowledge of the topic conducted the interviews in German to ensure objectivity. As food waste is a very sensitive topic and can affect a retailer's reputation (see, e.g., Hermsdorf et al., 2017), the interviews were not recorded for reasons of confidentiality. While the lead interviewer guided the conversation, the second transcribed the answers verbatim. Directly after the interviews, protocols were first compiled by each interviewer individually and then jointly reviewed. This is acceptable as in our case *how* anything is said is irrelevant.

Data analysis Our inductive analysis is neither driven by deductive logic nor follows a strict grounded theory approach (Randall and Mello, 2012; Manuj and Pohlen, 2012) because "data is inextricably fused with theory" (Alvesson and Kärreman, 2007). We adopted an interpretive research approach, which, in interpreting concepts in a first-order analysis, gives voice to the managers designing specific practices (van Maanen, 1983). Following this, we as researchers formulated deeper, more theoretical, and conceptual second-order interpretations (Bryman and Bell, 2011). The interview transcripts were subsequently analyzed in two layers. First, an objective content analysis was conducted to identify waste mitigation options, barriers, and impact. After establishing the options identified from the content analysis in the first layer, the second layer of analysis required the deconstruction of the data to extract tacit knowledge from the interviews. The second layer was a subjective analysis focusing on the rationales and effects behind the options. This allowed us to extract their underlying reasons and interrelationships along the SC to understand why the options are implemented, why they are thought to impact waste, and why barriers exist. Furthermore, we established a broader perspective on food waste strategies by collecting market data. This enabled us to inform the interview guide and validate the findings gathered. Websites, strategy statements, annual reports, etc., were scanned for food waste initiatives and facilitated discussions about the categories that emerged from the interview data later on. We used the data collected as an additional data source to substantiate our constructs.

The advanced interview notes were coded and categorized after each interview using MAXQDA 11. The advanced notes were rephrased, reflected on, and compared to create meaningful categories (Eisenhardt, 1989; Trautrims et al., 2012). Two researchers coded the data independently to provide the external validity of our findings. Codes were assigned to reflect interviewee descriptions. Each code was linked to a phrase from the interview transcript. This enabled complete traceability from an individual code to the advanced interview notes (Gioia et al., 2013). If a description or view did not fit a code already assigned, a new code was assigned to this item. 515 individual passages were coded (see Table 3.A2 in the Appendix). Interviews were conducted and initially transcribed and coded in German. Two bilingual researchers independently translated the codes into English and independently back into German (see Brislin, 1970, 1980). The authors then resolved any differences in the interpretation of the documents. Afterwards, we compared and discussed the codes and the emerging data structure to ensure external validity of the findings (Lincoln and Guba, 1985; Guba and Lincoln, 1989). This included a continuous comparison of codes in the researcher group to reach an objective hermeneutics approach (i.e., an intersubjective development of interpretive patterns). At regular meetings, all authors discussed the codes and findings to set aside subjective impressions from only one author and derive an objective meaning of interviewee perceptions. As a result, 21 distinct prevention and reduction options and 14 distinct barriers emerged from our analysis. We define an option as any potential retailer activity in SC planning to mitigate food waste. Each option identified represents a distinctive category. Subsequently, passages within the same category were analyzed to identify relevant patterns. Within this step, subcategories (also called subcodes) were defined by a mixture of deductive and inductive procedures. This means that the sub-questions in the interview revealed some subcategories while others were extracted from the material. The subcategories represent the barriers and impact of each practice. Next, we matched the identified options to the different stages of a grocery retail SC. Finally, we moved the empirical findings to theoretical insights by further conceptualizing them in two ways. First, we applied an aggregation of the 21 options concerning rationale and effect. This conceptualization allows us to obtain commonalities, mutual dependence, and interrelationships of categories. Second, we conceptualized implementation patterns for each option based on the interplay of the implementation level, barriers, and expected impact.

All authors discussed the codes, categories, conceptualizations, and ultimate findings at regular meetings to set aside subjective impressions and come to an objectivity of interviewee perceptions to ensure the external validity of our insights. Internal validity was achieved via triangulation with different data sources and confirmation checks with the interview partners (Lincoln and Guba, 1985; Guba and Lincoln, 1989). For example, we discussed intermediate findings at different stages of analysis with the interview partners. Furthermore, we participated in panels with retail experts, some of whom had also participated in the interviews. This feedback was incorporated into our findings.

3.4 Empirical findings

This section presents the empirical findings along different options to prevent or reduce food waste. We define an option as any potential retailer activity in SC planning to mitigate food waste. The options identified can be structured along the up- and downstream retail internal SC visualized in Figure 3.2. Upstream stages include all forecast-driven planning activities until the point of sales. These are proactive measures targeted at *preventing* food waste. Crossing the decoupling point that also separates forecast-driven from order-based planning activities, the downstream stages include all activities to *reduce* existing overstocks. The first stage is **inbound logistics (a)** as the interface between suppliers and a retailer. The second stage combines **warehousing & distribution (b)** as retail-internal storage and transportation processes. Subsequently, products enter the store. As the decoupling point in retail planning is located at the store, this stage is divided into **upstream store operations (c)** and **downstream store operations (d)**. **Salvaging (e)** complements this process as a last stage and as an interface to secondary channels, disposal, or other processors.

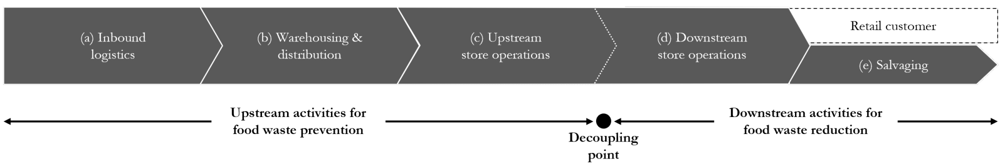


Figure 3.2: Scope of this study: Retail internal SC stages

Each option was described in the interviews as a dedicated mitigation effort and coded accordingly. We will elaborate on all options stage by stage to answer our research questions. We do so by analyzing *"how"* and *"why"* waste is prevented or reduced respectively. This is differentiated into two main operational effects identified: lower inventory levels and thus the reduced risk of overstocks, and faster throughput times from supplier to customer that extends the sales window in the store. We further highlight the expected impact, implementation levels, and main barriers that hinder the realization of each option. The major findings are highlighted in the summarizing Table 3.2.

Option	Rationale	Effect: Inv.[1a]	Time[1b]	Impa.[1c]	Impl.[2]	Main barriers
(a) Inbound logistics						
(a.1) Sourcing approach	Higher supplier reliability; more inbound transport bundling	↓	↓	med	low	Supplier dependency; competitive pressure
(a.2) Supplier collaboration	Higher supplier reliability	↓	—	med	low	Supplier dependency; IT integration; data quality; data protection regulation
(a.3) Inbound product flows	Shorter lead time by DSD More frequent deliveries by CD	↑ ↓	↓ ↓	high	med	Supplier dependency; processing costs
(a.4) Minimum order quantities and pack sizes	Aligning minimum order quantities and pack sizes to demand	↓	—	med	med	Supplier dependency
(a.5) Order cycles & volumes	More frequent deliveries; higher accuracy of demand forecasts	↓	—	high	low	Supplier dependency; incentive misalignment; processing costs
(a.6) Quality inspection	Higher supplier reliability; prioritized distribution of flawed products	↓	—	high	med	Processing costs; subjectivity of quality assessment; IT integration
(b) Warehousing & distribution						
(b.1) Delivery pattern	More frequent deliveries to stores	↓	↓	high	low	Processing costs
(b.2) Push allocation of warehouse stocks	Early distribution of emerging overstocks prolongs sales time window	—	↓	high	low	Inventory transparency; data quality
(b.3) Picking operations	Decreasing storage time and increasing sales time window	—	↓	low	low	Inventory transparency; processing costs
(b.4) Transship- ment btw. stores	Demand pooling across multiple stores	↓	—	low	low	Inventory transparency; processing costs; network density
(c) Upstream store operations						
(c.1) Assortment sizes	Pooling demand; improving forecasting accuracy	↓	—	very high	low	Competitive pressure
(c.2) Imperfect produce	Decreasing food loss at the agriculture and processing stage	↑	—	low	med	Cannibalization effect
(c.3) Differentiating service levels	Decreasing permanent availability; leveraging substitutions between products (pooling demand)	↓	—	very high	low	Competitive pressure
(c.4) Forecasting store demand	Improving forecasting accuracy	↓	—	very high	very high	Data quality; IT integration; employee qualification and motivation
(c.5) Shelf merchandising	Product arrangement using the FEFO principle	—	↓	high	high	Processing costs; employee qualifications and motivation
(d) Downstream store operations						
(d.1) Food waste monitoring & analysis	Increasing transparency about root causes and its analysis	↓	—	very high	very high	Data quality; employee qualification and motivation
(d.2) Discounting of overstocks	Demand stimulation by expiration-date-based pricing	—	↓	very high	very high	Processing costs; cannibalization effect; brand image
(e) Salvaging						
(e.1) Further processing internally	Refinement of products	—	—	med	med	Processing costs; food law regulations
(e.2) Take-back agreements	Supplier returns; incentive for stronger collaboration	—	—	low	low	Processing costs
(e.3) Secondary channels	Salvaging overstocks	—	—	med	high	Processing costs; food law regulations
(e.4) Donations	Salvaging overstocks	—	—	very high	very high	Processing costs; food law regulations

[1a,b,c] Decrease (↓) or increase (↑) of [a] lot sizes and overall inventory at the retailer's SC (incl. safety stocks) and [b] total throughput time from supplier to customer; [c] Expected overall impact on food waste
[2] Implementation level indicated by share of retailers who report the option as implemented at a percentage of 0-25% as low, 25-50% as medium, 50-75% as high, and >75% as very high

Table 3.2: Analysis of prevention and reduction options identified along the retail internal SC stages

3.4.1 Inbound logistics

(a.1) Determination of sourcing approach Food waste aspects can be incorporated into the retailer's sourcing approach when selecting suppliers and sourcing regions. Reliability, lead time, and logistical terms are important factors for prevention. DC03 describes this as follows:

"Transport routes and distances as well as the great variety of logistic chains should be more closely investigated in the context of food waste." (DC03)

The longer the lead time and the less reliable the suppliers are in terms of delivering on time and in full, the more the retailer is forced to build up safety stocks to hedge against uncertainties during the lead time – which is critical when perishable products are involved. In all cases, higher inventories result in a higher risk of food perishing and food waste being generated. The sourcing region additionally influences the lead time. The higher the transportation distance of products, the more orders need to be bundled, and lot sizes increase, and the less shelf life remains when products reach the shelves. A longer lead time also materializes in higher safety stocks that bear a higher risk of perishing. Fewer suppliers and sourcing regions lead to bundling effects in inbound transportation. This is beneficial as it allows a higher delivery frequency, resulting in smaller order sizes and decreasing the risks of overstocks. Despite these effects, the alignment of the sourcing approach has not yet been used actively for prevention in current practice. Decisions in this area are dominated by negotiations on purchase prices and product proliferation with more suppliers and sourcing regions as natural concomitants.

(a.2) Supplier collaboration An important aspect of preventing food waste through supplier collaboration is data sharing between suppliers and retailers. It increases transparency and logistics efficiencies for both parties. Especially in times of potential shortages due to SC disruptions, retailers need to hedge against the uncertainties with higher safety stocks, but these are prone to convert into waste over time. A lack of information sharing towards the supplier is even more critical in this context. *"A continuous information chain would be the goal to improve forecasting accuracy for the supplier,"* concluded SM02. Access to sales, order, stock, and retail forecasting data improves the forecasting accuracy of suppliers and minimizes waste at the supplier stage WRI (2019). Yet interaction efficiency is limited by supplier dependency, lacking IT integration, poor data quality, and data protection regulation. Strong supplier collaboration for food waste prevention has not yet been comprehensively put into practice. Only one out of four retailers considers that supplier collaboration enables them to achieve a higher control span and more reliable operations to be used for stock reduction and waste prevention. The low implementation level might be explained by the fact that suppliers gain greater benefits from this initiative.

(a.3) Selection of inbound product flows On a strategic level, retailers optimize the inbound flows for each product type and supplier by determining either direct store delivery (DSD), cross-dock delivery (CD), or warehouse-to-store delivery. DSD and CD are applied to reduce transportation and storage duration. *DSD* is beneficial for high-volume and ultra-fresh products that perish quickly (e.g., fruits & vegetables). For this product flows, further consolidation is usually not useful as the transportation capacities are fully utilized (e.g., full-truckloads (FTL)), and replenishment cycles are short (e.g., twice a day). This decreases total transportation time and reduces throughput time by direct deliveries to the store. This goes along with higher transportation and instore processing costs of DSDs. Furthermore, *"suppliers with DSD request high minimum order quantities that result in high inventories at the store"* (SM01). *CD* is based on high delivery rhythms: *"We order daily, sometimes even twice a day and especially during seasonal peaks"* (HM02). Storage periods become shorter with high delivery frequencies and short replenishment cycles. However, shorter cycles and smaller volumes do not allow for benefiting from order consolidation over time to achieve FTL deliveries. Utilizing capacity for long-haul transportation becomes a challenge. In this case, consolidation across suppliers is beneficial for less-than-truckload (LTL) deliveries. CD inbound flows enable the bundling of transportation flows of products across sourcing regions and suppliers, particularly for products with smaller order volumes and high delivery frequencies. The high delivery frequencies may also result from product requirements and short product life cycles. By skipping storage, CD operations decrease throughput time and allow a longer sales window but require efficient communication and coordination. The share of CD deliveries can be increased by strictly specifying time windows for ordering and delivery. Both DSD deliveries (reducing lead times) and CD deliveries (increasing delivery frequency) can contribute to the prevention of waste as they reduce throughput time. HM02 highlights this:

"The selection of suitable inbound flows for products is crucial as shelf life is consumed by stock-keeping." (HM02)

One-third of the retailers consider product flow selection as an option to prevent waste. However, DSD and CD have limited supply flexibility and increase supplier dependency compared to warehouse deliveries. Furthermore, the resulting higher inventory levels by DSD, increased coordination effort for both DSD and CD and potential cost increases have to be taken into account.

(a.4) Optimization of minimum order quantities Suppliers usually optimize minimum order sizes and packaging quantities based on their production and transportation needs across all their customers. This is not optimal for each retailer if minimum order sizes and package units are not aligned (e.g., for slow-moving products). Minimum order sizes or case pack sizes that are too large obviously mean that the retailer needs to order more units than the expected demand and orders less frequently. Both options are prone to increase waste. This is asserted by DC03:

"You can control a lot via purchasing modalities, and the subsequent implications are also interesting." (DC03)

Half of the retailers report targeted (re-)negotiation based on feedback on logistics and sales operations as a *"continuously ongoing topic"*. A higher impact of the retailer on the inbound SC (e.g., for own-brand production) enables retailers to negotiate about tailoring minimum order quantities and package sizes to actual demand in the retailers' stores and hence avoid food surplus. As negotiations along with operational changes are not necessarily in the interest of suppliers, limited market power restricts this option.

(a.5) Determination of order cycles and volumes Even if minimum order quantities are aligned, the order volumes and corresponding cycles may diverge, with larger lot sizes being ordered on a regular basis. Economically optimal order cycles and quantities are based on costs for order replenishment and inventory holding concerning shelf life, quantity discounts, prices that vary over time (e.g., for promotions), trade terms, and limited storage capacity in the warehouses. High transportation costs and misconceived incentives such as large quantity discounts tend to result in larger order volumes and even over-ordering. At this stage, *"sales targets are still more important than food waste decrease"* (DC04). SM03 mentions that the *"implications of ordering behavior on food waste are mostly unknown"*. A sustainability manager (DC04) even states: *"In the end, it's the personal preference of the purchaser that counts, so we only have an advisory role at this point."* This option counteracts waste minimization, where small order volumes and short order cycles are beneficial to decrease the total inventory level, and inventories are refreshed more frequently. A further major challenge is an unknown demand, as DC02 describes: *"The problem here is the order lead time. Procurement needs to know today what will happen two weeks from now."* Taken as a whole, these issues all indicate why determining inbound order cycles and volumes is currently not systematically leveraged to prevent food waste. Only one out of six retailers mentions this option in the context of food waste prevention.

(a.6) Quality inspection of incoming goods The monitoring of incoming goods comprises implementing *quality gates* and *thermal control*. *Quality gates* are assessments as to whether the predefined quality criteria (e.g., size, sugar content) are met. *Thermal control* is critical for all temperature-sensitive products and enables the detection of disturbances along the cold chain. If products with thermal issues enter the store, the risk of needing to discard these products increases. Almost half the retailers have emphasized the enforcement of quality standards and intensive controls. DC01 describes this as follows:

"*There is a high level of control, and poor quality is not accepted. It is better not to offer goods for one day than allow poor quality goods to enter our outlets.*" (DC01)

In this case, quality is weighted even higher than availability, at least on a short-term basis. However, the high manual effort and the subjectivity of quality assessment (e.g., for fruits & vegetables) are considered major barriers in this regard. Furthermore, thermal control requires the extensive application of temperature sensors and seamless IT integration. To summarize, rigorous quality control prevents waste occurrence at the retail stage but also leads to higher loss rates upstream. Suppliers are expected to adapt to the standards, decreasing the uncertainty for retailers (i.e., increasing supplier reliability) and allowing them to decrease safety stocks.

3.4.2 Warehousing & distribution

(b.1) Determination of delivery patterns Retailers limit delivery frequency to optimize distribution costs. They apply repetitive delivery cycles to level capacity at the warehouse and to ease warehouse, transportation, and store planning. A higher delivery frequency enables stores to align order volumes to daily sales volumes more efficiently and to order whenever replenishment is needed. Longer delivery cycles imply larger order sizes and higher stocks at stores. In addition, the forecasting horizon is longer, and the risk of forecasting errors increases. Both increase the risk of food waste. Delivery patterns also need to incorporate customers' shopping behavior:

"Our customers do their shopping once a week [...] Our philosophy is to offer fresh products that can be consumed until the next purchase." (HM02)

In summary, the delivery patterns optimize logistics systems, reduce logistics costs, align with customer shopping frequency, and need to factor in waste risk. Less frequent deliveries may lead to higher store inventory and have a negative effect on waste. An advanced approach considers the product life between two regular customer visits to prevent waste at the household level. Two retailers interviewed mentioned considering food waste aspects in delivery pattern planning but have not yet incorporated it into their current processes. The main barrier is increasing processing costs of a higher delivery frequency required to systematically prevent waste.

(b.2) Push allocation of warehouse stocks If stores order less than expected, higher stocks remain at the warehouse, and shelf life degrades over time. Push allocations of available stocks to stores have the potential to prevent deterioration and avoid overstock. This requires efficient inventory control. A basic approach is the distribution of stocks to stores equally or proportionally to the historical sales of these products. However, *"an equal allocation bears the risk of high losses for low-turnover outlets"* (DC03). The advanced approach is additionally based on current inventory and expected customer frequency on an outlet level. Retailer SM03 reports this as impactful:

"We developed a Big Data approach based on sales and inventory data. We know inventory ranges for each SKU and are able to allocate stocks to those stores with the lowest ranges." (SM03)

Waste is prevented as the sales probability at the stores increases with a higher remaining shelf life. To shorten throughput time and prolong sales periods in stores, 20% of the retailers currently apply an advanced data-driven option in this context. Real-time transparency on an outlet level and high data quality (e.g., inventory accuracy) are the prerequisites.

(b.3) Optimization of picking operations *First Expired – First Out (FEFO) picking* ensures that products that are the first to expire leave the warehouse first so that storage duration in the warehouse is minimized and the remaining sales time window before expiration is maximized. SM03 identified FEFO violations in warehousing & distribution as a driver for food waste in stores and described the situation as follows:

"We just recently gained transparency on expiration dates of products entering the store and observed FEFO violations far more frequently than we expected." (SM03)

Checking for FEFO is especially beneficial for products that are available in the warehouse in several different places (e.g., due to promotions). A further related picking process is *fraction processing* when single products or packaging units are damaged. Instead of directly disposing of the whole packaging unit, products are processed (unpacked, sorted, and cleaned) and allocated to stores at a discounted price. The benefits of preventing waste using fraction processing and FEFO picking are obvious, but both require precise inventory control and lead to additional handling and processing effort. Based on the low implementation rates (one-quarter of interview participants), apparently, the cost-benefit ratio of these options only appeals to some retailers.

(b.4) Transshipment between stores Redistribution of goods in the store network constitutes a short-term opportunity to proactively reallocate gradually emerging overstocks. When oversupply is recognized with accurate inventory control at an early stage, store managers may request redistribution. If stores with a higher probability of sales within the network can be identified, products are repacked and transferred to the closest stores with an additional demand. A surplus is prevented by pooling of demand across stores and hence can be materialized to lower total inventories in the system. However, this increases handling and transportation costs, as DC01 describes: *"Logistics costs eat up potential earnings."* As only one out of six retailers and exclusively discounters mention this option, it shows that application in the context of prevention is mainly relevant for retailers with a dense outlet network and shorter transportation distances between the outlets.

3.4.3 Upstream store operations

(c.1) Definition of assortment sizes Given the limited shelf space in stores, adding additional products to the assortment leads to lower shelf space for the products already listed. This increases the risk of fast-moving products running out of stock when their space and inventory are reduced, while additional slow-moving products that consume some of the limited space may remain unsold and expire over time. It also increases complexity for the upstream processes (e.g., warehousing) and susceptibility to lower forecasting accuracy due to substitutions and cannibalization. Consequently, assortment streamlining simplifies planning and prevents waste caused by forecast inaccuracies and slow-moving products. Moreover, a smaller assortment leads to a concentration of demand on fewer products (pooling), which ensures high turnover and consequently prevents waste. Three out of four retailers raise concerns that increasing variety leads to cannibalization, lower sales per product, and ultimately results in higher waste rates.

"We are heading in the wrong direction regarding food waste. If I provide every product type multiple times, I cannibalize myself." (DC03)

Despite the well-known negative effect of increasing assortment sizes on waste, none of the retailers currently use this option to achieve lower waste levels. It is *"only considered a theoretical option"* (DC03). On the contrary, interviewees across all store formats state that their assortment has increased in width and depth over recent years, with negative consequences on food waste, especially for the convenience segment and fruits & vegetables. At this point, product proliferation consciously compromises efforts directed at prevention, as DC03 summarizes:

"The spiral among competitors goes on and on. What is needed is a gentleman's agreement among retailers. Here, however, there is the problem of the prisoner's dilemma. The first to offer a broader assortment range wins." (DC03)

(c.2) Offering imperfect produce Retailers purposely deviate from strict appearance standards by offering imperfect produce. This produce is proactively labeled *"imperfect"* or *"ugly"* and offered at a discounted price. This is exclusively implemented for fruits & vegetables and decreases waste at the agriculture and processing stage. Half of the retailers interviewed have expanded their assortments with this product type. The main benefit lies in marketing opportunities targeting sustainability-driven consumers. In general, organic *"fruits & vegetables do not necessarily comply with the highest trade classes"* (OS02). Imperfect produce is, therefore, rather part of the strategic positioning for organic stores. Following the reasoning of assortment extensions from above, negative effects from a demand shift to less profitable products and the generation of waste from slow-moving products can be expected.

(c.3) Differentiating inventory service levels To compensate for short-term demand fluctuations in the event of inaccurate demand forecasting and to create an enjoyable shopping experience, strategic oversupply ensures full shelves for the customer. This inevitably leads to an emerging surplus of fresh and ultra-fresh products with a very short shelf life. Service level reduction is obviously an important lever for prevention. As all retailers confirm, low service levels bear the risk of unsatisfied customers and loss of sales, whereas high service levels may result in a surplus, high costs of inventory, and, ultimately, waste. Therefore, only one-quarter of the retailers mention the general service level reduction as a current waste prevention measure. General availability is still an important strategic goal; most retailers keep their general service levels high and see *"write-offs as a conscious investment in availability"* (SM03). This is expressed by SM03:

"There is brutal competition on the market: out-of-stock situations are not tolerated." (SM03)

Driven by the high customer expectations of availability and the fear of revenue loss in a competitive market, retailers are hardly willing to accept out-of-stock. Especially store formats targeting customers purchasing groceries in bulk once a week report the necessity of product availability, even during off-peak hours. An advanced option of that is switching from a single product service level to a *service level for product groups*, meaning that substitution effects between similar products are considered. Another approach is *time-dependent service levels.* The two organic stores interviewed are more liberal regarding their service level policy as their customers are more likely to accept slightly lower availability.

(c.4) Forecasting of store demand Demand forecasting is a core task of any replenishment system. Automated forecasting is considered a powerful tool to improve forecasting accuracy and prevent waste. The option is widely used in grocery retail practice, and *"high-profit potential"* is expected (ReFED, 2018, p.15). The interviewees report several factors to be considered, such as marketing campaigns, weather, or seasonality. DC02 summarizes the complexity: *"Customer buying behavior is anything but linear and cannot be anticipated easily. It is like crystal ball gazing and does not follow any regularities."* The retailers state that automated systems are superior in matching supply and demand compared to store personnel placing orders without any advanced automated disposition system.

"The human factor is further reduced and converted into a control function. The automated forecasting system is supposed to take over." (SM02)

Almost all retailers have an automated forecasting module in place, even though automation and store autonomy differ widely between retailers. There are five levels:

[1] *Fully manual order*: Store employees place orders based solely on experience without further data support or order proposals.

[2] *Basic order support*: Store employees receive order support but still need to decide autonomously what order quantity to place.

[3] *Proactive ordering proposal*: An order proposal is provided but needs to be actively confirmed by store employees.

[4] *Exception-based automated ordering*: This is already fully automated, but store employees still have the opportunity to modify orders in exceptional cases if needed.

[5] *Fully automated ordering*: Any intervention is excluded, meaning that store personnel cannot modify the order anymore.

The implementation levels vary between product segments for all store formats. For ambient products with a long shelf life, chilled and frozen products, almost all retailers have at least level [3] or [4] in place. For fresh products, most retailers only work with level [2] or even [1]. Only one retailer claims to have reached a higher degree of automation for fruits & vegetables. No retailer has so far implemented level [5]. As the different implementation levels indicate, retailers face various challenges. A major barrier is the lack of IT integration along with poor data quality, as DC01 summarized it with *"automated forecasting only works with good inventory management as a data basis"* (DC01). The human factor plays an important role, as DC03 concluded:

"Creating an understanding that employees should intervene less in the replenishment process and invest more time in data management is crucial." (DC03)

Furthermore, a solid understanding of the operating principle of the system for order proposals is crucial to avoid unnecessary interventions. However, employee willingness to change and their lack of trust in algorithms impede the transition towards further automated systems. In addition to that, especially larger retailers with diversified store concepts report that significant store heterogeneity also leads to challenges, as a one-size-fits-all approach is no longer sufficient.

(c.5) Shelf merchandising and arrangement Executing a strict *FEFO shelf arrangement* at stores prevents waste. Products with shorter expiration dates are placed at the front before products with longer expiration dates, intending that customers withdraw the units in the front rows. This manual task is usually executed at the same time as refilling the shelf. As customer withdrawal might disrupt this desired arrangement (e.g., by withdrawing fresher products), *"product circulation"* (HM02) and continuous inventory control are necessary. In this respect, three-quarters of retailers consider employee qualifications and motivation as pivotal for waste prevention. *"Training of staff in temperature management, product handling, and stock* *rotation”* (WRI, 2019, p. 17) is a general requirement for preventing food waste. Although retailers are aware of the positive impact of employees on waste, training is an ongoing investment and cost factor due to the high industry-specific employee fluctuation rates.

3.4.4 Downstream store operations

(d.1) Monitoring and analyzing food waste Transparency on food waste is essential to analyze root causes and steer operations to prevent waste upstream of the SC and reduce it downstream of the SC. Almost all retailers report that they have monitoring in place and know the write-off quantities for every product in every store per day.

“We have various analysis options in our ERP system to identify and process write-offs. If they are suspiciously high, problems are investigated, and countermeasures derived.” (HM02)

Even though total write-off quantities are known, the causes are often not sufficiently specified. None of the retailers systematically differentiate written-off quantities into actual waste (e.g., disposals) and subsequent use (e.g., use of secondary channels). DC03 considers the *“employee qualification as a major barrier for valid data”*. DC04 highlights that *“data currently does not allow deeper insights”*. Therefore some retailers estimate actual waste by the number of bins or based on samples, but this only provides limited accuracy.

(d.2) Discounting of overstocks Retailers can stimulate demand by expiration-date-based pricing of overstocks. All retailers interviewed apply the sale of products at discounted prices at different periods to salvage emerging overstocks as DC02 expresses: *“Price adjustments are incorporated* *in everyday store life and anchored into our standard work processes."* The process is described across all participants as a manual effort. Discounting guidelines differ between formats and product segments. While discounters deploy a simple one-time discount of 30% or 50% three days before the best-before or use-by date, other retailers rely on two- (e.g., 30/50%) or even three-stage (e.g., 30/50/70%) discounting over time. Almost half of the retailers mention the store manager's autonomy as an important lever.

"They are allowed to discount on their own and place items twice [...]. However, this may not be every time, so they are supposed to learn from it." (DC02)

The store manager's role is more of a reactive control function rather than a proactive one. Of course, processing costs, lower margins, consumer perception, and implications at the consumption stage have to be considered. *"It has to be calculated very precisely which products are eligible for a discount. Sometimes it is not worth printing the label, for example, if you have a product that has already been discounted"* (DC04). If the remaining margin after discounting is extremely small, retailers are afraid that price reductions are not the most economical option. Furthermore, excessive price cuts might harm the brand image concerning freshness and lead to cannibalization effects. This is why leftovers are often placed separately in a dedicated area for discounted products. Besides the economic trade-off, DC03 raises the concern of triggering food waste in households:

"If the customer buys because of an 80-90% discount, food waste may just be passed on to the next stage. We are responsible for not discounting too much. While aiming for profit, we do not want to set the wrong trigger for the customer." (DC03)

Nevertheless, discounting overstocks as a food waste minimization option is set to gain even greater importance in the future. Discounting still represents an option to salvage overstocks that would otherwise stay instore for extended periods. Almost one-third report ongoing automation efforts.

"In the future, the process of dynamic discounting needs to be automated. Store-specific, product-specific, time-sensitive marketing mechanisms are a great lever [...]. Automatically optimized and not subjective according to the assessment of the specialist on-site. With the prerequisite of digital price tags, prices could change several times a day." (HM01)

This requires real-time transparency on inventory levels and past and expected sales (ReFED, 2018). Currently, there are early development projects, mainly to improve data quality.

3.4.5 Salvaging

From a retailer's perspective, options at the last stage constitute minimization strategies with the objective of salvaging surplus. All these options shorten storage time at the store and increase the probability of consumption. A thorough trade-off between economic, social, and environmental benefits must be considered as they induce additional process costs or lower revenues. Furthermore, some regulatory barriers (e.g., sales before the best-before date) need to be respected. The impact on waste is no longer related only to proactively reducing inventory levels and throughput but to salvaging accumulating inventories in the most economical, ecological, and social manner.

(e.1) Further use internally for food processing Further instore processing is only possible if the store offers ready-to-eat products and has space within the store. Soon-to-expire products are removed from the shelf early on and brought to backroom kitchens. Waste is reduced if the sales probability of the further processed product is higher than the soon-to-expire ingredients. However, OS02 reports economic and regulatory limitations in this regard: *"Processed products must be clearly labeled. The effort required is not always worth it."* The processing effort and strict regulatory framework for further processing might explain why only one-third of the retailers apply this option.

(e.2) Implementation of take-back agreements Contractual arrangements with suppliers may mean that the retailer only pays for products that customers actually buy, and all remaining quantities can be returned. They are exclusively implemented for bread and pastry products at one-quarter of the retailers. They obviously reduce food waste at the retail stage, but as the cost of unsold products and logistics are considered in purchase prices, retailers still pay indirectly for waste. The problem may only be shifted. Nevertheless, this provides incentives for stronger collaboration to align processes, order cycles, and minimum order quantities.

(e.3) Sales through secondary channels Six out of ten retailers leverage *secondary channels* to salvage leftovers like residual stock dealers who buy overstocks at large scale, headquarters canteens, and other market segments. While the two options first mentioned are only reported in one case each, and applicability for both was limited due to processing costs, cooperation with a third-party service provider is consistently reported across all formats. Even though the concept is ecologically beneficial, there are regulatory obstacles with labeling and costs for the retailer arise due to instore handling and packaging. Since products can only be sold at a massively discounted price, several retailers report the option as economically questionable (see also ReFED, 2018).

(e.4) Donation of charitable food Food banks pick up donations once or several times a week and redistribute them to people in need. It is often considered a last resort.

"If all else fails, then we work with food banks or other local organizations." (HM02)

Except for one, all other retailers report collaboration with charities. However, market data indicates that only a small proportion of unsaleable food is donated, e.g., only 18% in the US (FWRA, 2016). Consequently, there is still a *"significant opportunity to increase donations through higher store and distribution center coverage and donation capture rates"* (ReFED, 2018). This may be explained as labor costs for providing products and documenting the process outweighing the savings in disposal costs. Regulations are the main limitation for further waste mitigation at this stage (see also ReFED, 2018). *"Donations are mainly limited to fruits & vegetables and bread because fresh meat and dairy products are problematic in terms of liability"* (DC02). DC01 even states: *"I would never do this because I would be liable for putting it on the market."*

3.5 Results and discussion

This section develops the empirical findings towards a generalization and conceptualization. This allows us to transfer the empirical findings obtained from the field into theoretical concepts for preventing food waste in retail SCs.

3.5.1 Conceptualizing the food waste prevention and reduction options

This section derives propositions for the prevention of food waste from our empirical findings. For this, we first use the categories developed above (namely the 21 options identified) and aggregate them to a higher level with regard to our research questions and *"how"* and *"why"* waste is minimized. This conceptualization allows us to obtain commonalities, mutual dependence, and interrelationships of categories. We then develop a framework for food waste minimization in retail SCs by aggregating the options into five main areas (see Table 3.3). The main areas enable us to generalize the prevention strategies for retailers and consequently derive targeted propositions. The first three areas concern proactive prevention measures to lower inventory levels in the retail SC. The fourth area deals with proactively managing throughput time, whereas the last one is related to salvaging emerging overstocks.

Area (*how*)	**Rationale** (*why*)	**Related options**[1,2]
(I) Decreasing inbound lot sizes	Smaller order volumes and minimum order quantities enable more frequent refreshing of inventories.	(a.4) Min. order quantities and pack sizes (a.5) Order cycles & volumes
(II) Decreasing total inventory by pooling demand	Differentiated service levels, streamlined assortments, and transshipment across stores pool demand which enables lower total inventory levels.	(b.4) Transshipment between stores (c.1) Assortment sizes (c.3) Differentiating invent. service levels
(III) Decreasing safety stock levels	Increasing SC transparency, reliability of suppliers and internal processes, and forecasting accuracy reduce uncertainty in the SC and, consequently, safety stocks.	(a.1) Sourcing approach (a.2) Supplier collaboration (a.6) Quality inspection (c.4) Forecasting store demand (d.1) Food waste monitoring & analysis
(IV) Increasing the time window for sales at stores	Limited warehouse storage, higher delivery frequencies, and optimized stock allocation and picking reduce throughput time and ensure a higher remaining shelf life.	(a.3) Inbound product flows (b.1) Delivery pattern (b.2) Push allocation of warehouse stocks (b.3) Picking operations (c.5) Shelf merchandising
(V) Salvaging emerging overstocks	Forward-looking mitigation processes reduce accumulating inventories before they become waste.	(d.2) Discounting of overstocks (e.1) Further processing internally (e.2) Take-back agreements (e.3) Secondary channels (e.4) Donations

[1] Some options impact multiple areas. To simplify the overview, options were only allocated to their main area.
[2] Offering imperfect produce (c.2) increases inventory at the retail stage and is therefore not considered

Table 3.3: Framework for food waste minimization in retail SCs

Area (I) compromises prevention options that factor in overstock risks and food waste aspects for **decreasing inbound lot sizes** to reduce average inventory levels. Lower stocks lead to lower inventory reach, which is of the utmost importance for slower-moving products. At the same time, smaller lot sizes result in more frequent replenishment and shorter risk periods. This lowers the risk of perishing inventories and emerging overstocks. It can be achieved with optimized minimum order quantities and pack sizes as well as shorter order cycles, both in close and constant alignment with suppliers. All options in this area are related to decisions in inbound logistics but impact inventory levels in the entire internal retail SC. These findings result in the first proposition (P):

P1: Reducing the risk of overstocks via adapted order modalities and cycles according to retailers' actual demand prevents food waste across all stages of the internal retail SC by decreasing inbound lot sizes.

Area (II) conflates the prevention options for **decreasing total inventory by pooling demand**. Considering demand substitutions in assortment and inventory planning allows smaller assortments and lower specific inventory service levels. For example, slow-moving products bear a higher risk of perishing. When these products are delisted, or lower service levels are applied, customers may substitute the unavailable products with alternative products such that the demand is transferred. An advanced option is therefore switching from an individual product service level to a time-dependent service level for product groups. This still ensures the targeted strategic oversupply for certain products. The resulting demand pooling enables more efficient use of available inventories without having a major compromise on customer preferences. Transshipment between stores constitutes a further pooling effect as demand is fulfilled on an aggregated level and not just the store level. In all these examples, taking effect in warehousing & distribution and store operations, customer demand may still be satisfied, but at lower overstock levels, and food waste is proactively prevented. This allows us to formulate the second proposition:

P2: Pooling demand via targeted customer steering (assortment and service levels offered) and inventory balancing (transshipment) prevents food waste by decreasing total inventory levels.

Decreasing safety stocks constitutes Area (III). High safety stocks induce a high risk of product expiration, but they are necessary to hedge against uncertainties about the quantity or time at which products are available and demanded. Reducing the variability of lead time, quality, delivery quantities, and demand uncertainty enable lower safety stocks. Investments in forecasts, quality control, and supplier collaboration are examples of prevention options that increase the reliability of inbound logistics and store operations. These insights are summarized by our third proposition:

P3: Decreasing uncertainties via advanced internal and external collaborations (transparency, process alignment, and supplier collaboration) and improved forecasts prevents food waste by decreasing required safety stocks.

Area (IV), **increasing the time window for sales at stores**, comprises all options that maximize the time products are available for sale at stores. Retailers can proactively prevent food waste by increasing the time window for sales by minimizing the throughput times from suppliers to the store shelf. This can be achieved by limited warehouse storage duration, higher delivery frequencies, and optimized stock allocation and picking. If products are processed faster throughout the SC, product life is less consumed with transportation and storage. This increases the sales period and probability of products being sold before expiration. Moreover, a short throughput time allows flexible adjustment of orders and shortens the forecasting horizon, which limits the risk of forecasting errors. Options in this area range from inbound through warehousing & distribution to the stores. The fourth proposition in regard to throughput times is formulated as follows:

P4: Prolonging a product's time in the store via optimized warehouse operations (storage time, picking, and stock allocation) and frequent deliveries prevents food waste by increasing the sale's probability.

Finally, Area (V) is **salvaging emerging overstocks** at downstream stages of the SC. Options allocated to the last area are forward-looking mitigation processes targeting accumulating inventories before they become waste. All options, however, go along with lower margins and can only be realized as long as sufficient best-before dates are maintained or processing and discounting costs do not exceed the remaining economic, social, or environmental benefits. Therefore, all these options require an early and forward-looking intervention. Otherwise, products may not be used further, for example, for discounting and donation due to too close best-before dates. Following these findings, we formulate the corresponding proposition:

P5: Intervening in due time when inventory levels increase via dedicated countermeasures at stores (discounts and alternative usage) prevents food waste by mitigating emerging overstocks but requires a careful trade-off between economic, social, and environmental benefits.

This analysis shows that the options cannot be seen in isolation. They reinforce each other and require interrelated consideration across the SC. For example, assortment reduction (c.1) goes along with the sourcing approach (a.1), inbound product flows (a.3), shelf merchandising (c.5), and order cycles & volumes (a.5), and hence affects the SC stages inbound, warehousing and store, and as such Areas (I) to (IV). Consequently, it is not sufficient for retailers to optimize only selected parts of the operations without considering the up- and downstream implications. We, therefore, derive a concluding proposition:

P6: Taking into account the interdependence of retail SC stages is essential to prevent food waste as it allows a concerted planning approach and avoids shifting food waste issues to other stages.

3.5.2 Conceptualizing implementation patterns

We further conceptualize our findings to reveal *"why"* certain options are more frequently implemented than others. By analyzing implementation levels, existing barriers, and expected overall impact, we are able to aggregate the options into five distinct patterns. As food waste strategies are retailer-specific, we found no evidence for a sequential order of steps taken. However, we found distinctive implementation patterns. Each pattern compromises a set of related options. The implementation level indicates the share of retailers interviewed that report the option as implemented, while the barriers and the expected overall impact are based on the assessment expressed by the experts during the interviews. Within those three dimensions, we searched for commonalities and interrelationships between the individual options. Figure 3.3 summarizes five patterns that are developed below. Options within each pattern are sorted by implementation level in ascending order.

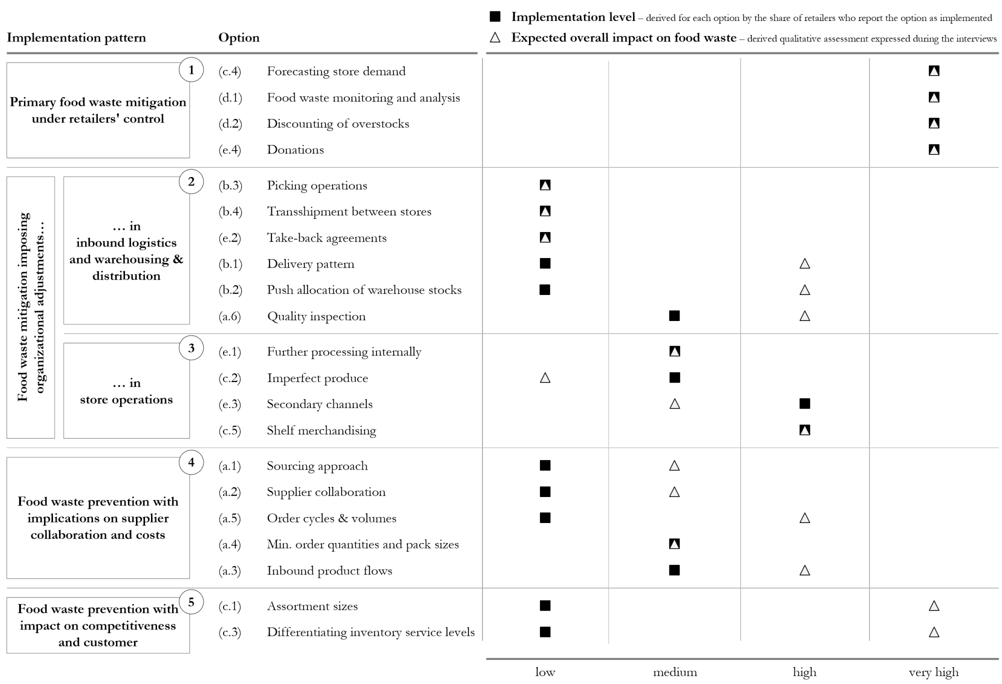


Figure 3.3: Conceptualization of implementation patterns

Pattern 1: Primary food waste mitigation under retailers' control Pattern 1 includes options with very high implementation and impact. The options monitoring (d.1), discounting (d.2), donations (e.4), and forecasting (c.4) are easier to implement as retailers do not need to compromise on availability, competitiveness, or costs. Barriers to these options are primarily internal (e.g., data quality, IT integration, or processing costs), meaning that implementation and execution lie (almost) exclusively in the retailer's hands. Furthermore, demand forecasting and monitoring anyhow go hand in hand with other tasks and daily business. The high relevance of discounting and donations is ascribed to both the high potential to reduce waste and the low organizational barriers. Both options can be executed on the store level and require only minor coordination effort and set-up processes.

Pattern 2: Food waste mitigation imposing organizational adjustments in inbound logistics and warehousing & distribution Options collated under this pattern are also within the retailers' sphere of influence but impose considerable organizational changes and processing costs, and thus they are currently not systematically implemented. However, the gap between low implementation and high impact on food waste for delivery pattern (b.1), push allocation of warehouse stocks (b.2), and quality inspection (a.6) indicates a potential development direction. The gap exists because retailers need to balance the benefit of lower waste with the increase in processing costs. Furthermore, poor inventory transparency, data quality, and IT integration still limit these options. For picking operations (b.3), transshipment (b.4), and take-back agreements (e.2), the low implementation might be explained by the high costs and lower expected potential to lower waste.

Pattern 3: Food waste mitigation imposing organizational adjustments in store operations The options in this pattern are also under the retailers' direct control. However, the options in the store are more used than those in the upstream parts of the SC. This might be explained by the fact that the impact of those options is closer to the point where waste finally occurs (i.e., the store). However, the reduction options further processing internally (e.1) and the use of secondary channels (e.3) need additional in-store capacities for processing and packaging and is subject to food law regulations. While shelf merchandising (c.5) is also cost-intensive but still highly impactful, offering imperfect produce (c.2) leads to cannibalization.

Pattern 4: Food waste prevention with implications on supplier collaboration and costs Most options at inbound logistics are limited by supplier dependency. However, the options with medium to low implementation paired with medium to high expected impact indicate that they have not yet been materialized but might gain importance going forward. For a shortening of the throughput time (e.g., inbound product flows (a.3)), the main barriers increasing logistics costs and required inventory transparency need to be addressed. Options for reducing inventory levels (e.g., order quantities (a.4)) and safety stocks (e.g., sourcing approach (a.1)) are mainly limited by suppliers' willingness to collaborate. Retailers need to establish a careful balance between supplier dependency, cost implications, and waste mitigation to materialize the waste savings potential.

Pattern 5: Food waste prevention with impact on competitiveness and customer Significant waste minimization cannot happen as long as service levels and assortment sizes are kept at high levels. Therefore, limiting the assortments (c.1) and differentiating inventory levels (c.3) are key levers to minimize waste. However, they are currently only contemplated but not yet largely realized. In a highly competitive market, retailers would need to sacrifice product proliferation and high on-shelf availability targets in favor of waste prevention. Waste and economic loss that occur are considered "investments" that are consciously accepted in the end. Under these premises, only a more sophisticated approach that considers the impact of assortment adjustments on waste and tailored product- or period-specific inventory service levels will allow reducing waste.

3.6 Conclusions

This section summarizes the findings, discusses the implications of our findings on literature and practice, and elaborates on limitations and future research.

Summary The growing need for sustainability puts food waste minimization at the top of the agenda of grocery retailers. We leverage primary market data and apply a view on retail operations that has not yet been explored in this regard. Preventing surplus before it emerges is the most ecologically and economic approach for retailers to minimize food waste. However, both retailers and research have been focused on reactive food waste reduction options in stores. Despite the expected high overall impact on waste, prevention measures in inbound logistics, distribution & warehousing, and upstream store operations have not been intensively applied to date. As the first empirical study to systematically investigate in the *"how"* and *"why"* waste is minimized, we present a novel framework for food waste prevention and reduction options within retail operations. Further, we lay a managerial foundation for retailers willing to tackle food waste by conceptualizing implementation patterns. Future priorities should include overcoming the barriers identified and incorporating food waste aspects across all retail SC stages as well as leveraging the power of data and advances in decision support.

Contributions to literature While current reviews and framework papers such as de Moraes et al. (2020), Akkaş and Gaur (2022) and Huang et al. (2021) use secondary data, we leverage first-hand insights from retail practice to reveal food waste prevention options. Our work contributes insights into how and why grocery retailers can prevent food waste within retail operations. We introduce a framework for minimizing food waste in retail SCs and derive propositions for proactive food waste prevention. The direct insights from the field allow us to analyze implementation levels and barriers, whereas current literature (see, e.g., Huang et al., 2021; Akkaş and Honhon, 2022) is based on secondary data sources, which limits the insights into the actual application and barriers. We conceptualize implementation patterns and identify a shift from reactive food waste reduction to proactive prevention. We are the first to identify and structure barriers for food waste minimization approaches.

Structuring prevention options along the retail operations enables us to identify the interrelationships and effects of the options. In line with prevailing literature (e.g., Huang et al., 2021), our empirical findings reveal that the retailers' focus is currently on reduction options at the store. This applies to different formats and store concepts. We identify further impactful prevention options upstream of the SC in inbound (e.g., sourcing approaches, optimization of inbound product flows) and warehousing & distribution (e.g., (re-)allocation of warehouse overstock). The potential to prevent food waste at the inbound logistics stage and in warehousing & distribution needs more attention. At the inbound stage, the focus in the literature has primarily been on improving supplier-retailer collaboration and joint forecasts (e.g., Kaipia et al., 2013; Liljestrand, 2017). The optimization of pack sizes and minimum order quantities is only based on operations efficiency in current literature and not on food waste aspects (see, e.g., Ketzenberg et al., 2002; Broekmeulen et al., 2017; Wensing et al., 2018). We highlight the impact of aligning minimum order quantities and pack sizes on avoiding food waste. Furthermore, our empirical findings show that a significant impact on preventing food waste is attributed to the optimization of delivery patterns or push allocations. This also needs to be reflected in related literature on warehousing & distribution.

The current empirical literature on food waste prevention at the store level concerns the role of the managers and the store managers' impact on food waste (see, e.g., Gruber et al., 2016; Filimonau and Gherbin, 2017). We highlight further options in planning upstream store operations (e.g., assortment sizes, differentiating service levels) and downstream store operations (e.g., monitoring, discounting). Here, we identify more advanced options for preventing store waste by leveraging data power and decision support advancements. Our interviews indicate a positive effect on waste prevention via a high degree of automation in forecasting. As multiple factors impact demand (e.g., seasonality, weather, etc.), systems with more automation appear to be superior to manual orders. The superiority of automated systems partially contradicts the findings of van Donselaar et al. (2010) and Horoś and Ruppenthal (2021) that indicate the positive impact of managers forecasting interventions. In line with empirical literature (see, e.g., Gruber et al., 2016; Teller et al., 2018), our findings confirm that discounting is a highly effective downstream option. Discounting is largely applied in retail practice but relies on rather simple guidelines. Our interviews reveal that analytical and optimization approaches, as proposed, for example, by Zhang et al. (2015) or Buisman et al. (2019), are not yet transferred to retail practice. More analytical approaches are expected to become effective with increasing data and computation power. We extend the discussion about discounting by adding the negative consequences of price cuts, such as customers' freshness perception and cannibalization effects. These findings call for advanced research to develop analytical and data-driven guidelines for discounting approaches.

Finally, high on-shelf availability remains an important strategic goal for retailers in the context of food waste minimization and sustainability goals. In contrast to the literature on out-of-stock avoidance, in which food waste is considered as a "cost of overstocking" to avoid empty shelves (see, e.g., reviews of Aastrup and Kotzab, 2010; Moussaoui et al., 2016), we show that the trade-off between additional sales and logistics costs when determining service levels must be enriched with substitution and pooling effects that minimize food waste. Furthermore, service levels should be more differentiated by time (e.g., closing hours) and rather on a product group level instead of individual products. We could confirm the findings of Moussaoui et al. (2016) and also show that the definition of service levels is context-specific and optimal levels are defined differently for different retail concepts (i.e., organic stores vs. regular grocery stores). Further, the food waste improvements at the different retail stages (e.g., shorter throughput time) or the supplier-retailer interface (e.g., higher transparency) are also expected to affect on-shelf availability positively. A stronger collaboration between retailers and suppliers will improve the on-shelf availability (see, e.g., Trautrims et al., 2009) and food waste prevention at the same time as an example.

Managerial implications Our empirical findings reveal critical managerial implications and enhance food waste management for practitioners. Using our insights and the prevention framework introduced, retailers obtain a structured approach to mitigate waste in their operations. Further, we categorize the types of barriers that retailers need to address to mitigate waste in retail operations. Experts emphasize the current need for further advanced options upstream of the SC due to their undeniable importance. This is particularly true for more differentiated assortment and service-level management approaches. Our findings indicate that three of the most impactful options (c.1, c.3, c.4) are not or only partially influenced by store managers. This highlights that managerial decisions on food waste prevention need to be mainly addressed on a corporate level with advanced options upstream of the SC. This means factoring in multiple aspects, including a total cost perspective, aligning incentives, and sharpening competitive positioning.

Experts attribute a significant impact on food waste to data analytics and quantitative approaches. One prominent example in this regard is the development of efficient discounting approaches. Retailers still use a simple discounting logic or even rely on subjective assessment due to the lack of decision support tools and limited data availability and quality. A further example is human trust in automated forecasts. This shows that data analytics is more than merely a technical issue and calls for adequately embedding analytical capabilities in the ecosystem to achieve a successful transformation. As implications for practice, we show that besides the data quality, employee qualifications and human trust to leverage automated systems are currently limiting factors.

Limitations and future areas of research Our focus was on the broad investigation and internal retail operations planning. The breadth of such an approach inevitably involves compromising on the depth of individual options. Dedicated studies on the effects of individual options on other SC stages and a more detailed analysis of individual stages and related options would be beneficial. Second, a detailed cost/benefit and life cycle analysis needs to be improved for comprehensively balancing options. Future research could quantify our exploratory findings. This should also be expanded to factor in environmental and social aspects. Furthermore, other aspects of minimizing food waste, such as packaging and cooling technologies, have not been analyzed. Packaging can protect food and prolong shelf life, thus reducing food waste and a product's environmental footprint (see, e.g., Verghese et al., 2015; Brennan et al., 2021). The same holds true for continuous cold chains (see, e.g., Akkerman et al., 2010). Third, our study analyzes the effect of SC planning to minimize waste. This study does not include further opportunities to influence customer behavior such as undesired withdrawal behavior (see, e.g., Hansen et al., 2023; Winkler et al., 2023b) or freshness-dependent demand (see, e.g., Chen et al., 2016). Steering customers in this regard with store operations constitutes a further research direction. Fourth, the research was conducted in Germany with international brick-and-mortar retailers. Although we expect the results to be transferable to other countries, a similar study of retailers from diverse countries could be the next step. As online grocers are on the rise and more retailers are considering an omnichannel setup, future research should adopt our study to identify channel-specific differences. Last but not least, our study provides a snapshot with respect to implementation levels and options. Longitudinal research could be conducted by repeating our results to analyze implementation patterns due to shifts in competitive pressure or consumer behavior.

Appendix

Approach for literature review

To ground our study in literature and later on to compare the identified options with existing research in retail operations, we perform a literature review. This ensures a comprehensible and objective process. We utilize a fourfold approach, starting with a keyword-based search on Scopus and Google Scholar in leading empirical journals in operations management, retailing, and sustainability. For the sake of focus, only peer-reviewed articles written in the English language that conduct studies in the context of food waste in grocery retail are considered. Initial screening and selection (including eliminating duplicates) are conducted by all authors based on title, abstract, and keywords. Subsequently, suitable articles are read and either included if they match the above-mentioned criteria or excluded.

The following search string was used to capture evidence in bibliographic database:
(retail* OR supermarket OR store OR shop OR grocer*) AND (reduc* OR prevent* OR avoid* OR minimi* OR optimi* OR decrease* OR lower* OR control* OR limit* OR manage* OR mitigat*) AND ("food waste*" OR "food surplus*" OR "surplus food" OR "food loss*" OR “wast* food”)

Second, the reference sections of selected articles were screened to identify further matching work (snowball method). Third, we use Google Scholar to analyze any articles that cited selected research from steps one and two to further find matching articles. Fourth, manual searches of leading journals in the field are carried out. This is comprehended with literature reviews related to food waste management. They are leveraged to obtain a broader perspective and get insights into research needs and gaps. As an outcome, we obtained 47 papers from these process steps. For inclusion in the literature review in Section 3.2, we only considered contributions dedicated to food waste mitigation in retail SCs. In order to ensure a retail SC perspective, we excluded consumer-focused studies (e.g., papers investigating consumer response to suboptimal products) and purely analytical and mathematical papers (e.g., reducing waste with dynamic pricing). Ultimately, the 11 empirical articles presented in Section 3.2 were identified to be the most relevant in regard to our research focus.

Interview guide

The primary function of the interview guide was to structure the discussion in two main sections. In the first section, we asked which prevention options are implemented at the retailer, how impactful they are and why, and which barriers to implementation exist. Since the actual impact of a specific option (e.g., in terms of food waste or costs saved) depends on the context and multiple dimensions, we asked for the relative impact of options. In the second part, we challenged the retailers' approach to gain insights into known options that had not been mentioned.

Part	Guiding question	Follow-up question[1]
Intro	Tell us about the general perception of food waste within your company?	How has this developed over the last 5-10 years?
(a)	Tell us about the most successful option/project to prevent food waste?	Why and how was the option implemented? What was the impact? How is food waste prevented? What barriers had to be overcome? Are there plans to expand or roll out the option, why and how?
	Tell us about other options to prevent food waste that have been implemented?	Why and how was the option implemented? What was the impact? How is food waste prevented? What barriers had to be overcome? Are there plans to expand or roll out the option, why and how?
(b)	Tell us how your company will further approach food waste prevention in the future.	Do you know of any other options to prevent food waste, e.g., in planning, distribution, etc.?
	Can you imagine, that food waste in grocery retailing could be completely avoided in the future?	What would have to change so that there is no more food waste? How will grocery retailing develop in this regard in the future and why?
	Are there any other important topics that have not yet been discussed?	

[1] Optional questions, to be included on demand

Table 3.A1: Guide for semi-structured interview

Coding scheme

Themes and categories	Representative data
Options {262}	
Assortment sizes	*We need to address the influencing factors. If done rigorously, we would have to monitor write-offs and unlist products where we do not succeed in reducing food waste. Customer services would need to go down* (HM02).
Delivery pattern	*A further lever is the adjustment of delivery patterns, e.g., through ultra-fresh warehouses in which perishable products can be processed in a short time* (SM02).
Differentiating inventory service levels	*At least one tomato variant must still be available in any case. Substitution effects are taken into account within the product groups. Availability indicators are both product and time specific: e.g., 95% on Saturdays and 97% on weekdays for the fruits & vegetables assortment* (DC02).
Discounting of overstocks	*Discounting is a common practice, however, still a completely manual process. The implementation depends on the time management of the store, but employees should have time for this* (SM02).
Donations	*We also cooperate with food banks. They come once a week and pick up the groceries. [...] We are also happy that we do not have to dispose it* (DC01).
Food waste monitoring and analysis	*In the past, the focus was mainly on the store, but today we focus on the entire supply chain. [...] A central unit monitors losses along the entire supply chain and acts as an advisor for procurement, forecasting, and replenishment operations* (SM02).
Forecasting store demand	*Great progress is expected through full automation and algorithms. Everyone is 100% convinced that it will get better, but it is unclear how far it can be pushed* (DC02).
Further processing internally	*Products close to the expiration date are removed from the shelves. There are several options for how products can be utilized. Each store has its own catering and kitchens. [...] Fruits & vegetables can be further processed to convenience products* (HM02).
Imperfect produce	*Offering imperfect produce reduces losses at the farming stage. Those products were marketed with several campaigns. However, customer acceptance is limited* (SM03).
Inbound product flows	*The decision of whether fresh products should be kept in stock at our warehouse is crucial. [...] An alternative is cross-docking, where the goods are only transshipped in the warehouse and then delivered directly to the store* (HM02).
Min. order quantities and pack sizes	*We are constantly in exchange with procurement to adjust order quantities and packaging. A good example is sausage products, where we only sell 60% on average. Then we have three options: unlist the product, waste the remaining 40%, or adjust the package size* (HM01).
Order cycles & volumes	*Lead times can be coordinated with the supplier to keep batches small. This reduces the stock and thus the risk of food waste, however, it is very costly* (WS01).
Picking operations	*FEFO picking in the warehouse ensures that first to expire products leave the warehouse first, with positive effects on the remaining shelf life* (SM03).
Push allocation of warehouse stocks	*A special case is product allocation, i.e., goods that have not been ordered but still need to be distributed to the stores because of decreasing shelf life. We try to allocate goods based on past turnover and store frequency* (DC03).
Quality inspection	*There is a separate department for quality control that inspects incoming goods based on predefined quality characteristics* (DC02).
Secondary channels	*Last resort is the sale to secondary channels, e.g., remnant dealers, where products are sold at a 70-80% discount* (WS01).
Shelf merchandising	*Especially highly perishable products are frequently checked. A new delivery must always be placed behind or below the old inventory. [...] Product circulation should be applied in each refilling process* (DC01).
Sourcing approach	*Supplier dependency also plays an important role. How reliable are my suppliers? It happens from time to time that trucks stop at the borders. [...] Weather but also transport routes might cause fluctuations in supply* (DC03).
Supplier collaboration	*Cooperation with suppliers is a good option. Here, forecast data is passed on to the processing industry. [...] Continuity of the information chain would be the goal, whether in competition or not. An interconnected supply chain would improve forecast accuracy* (SM02).
Take-back agreements	*In case inventory cannot be sold, returning batches to the processing industry is also an option. However, this depends on the supplier relationship* (WS01).

(continued on next page)

Transshipment between stores	*Exchanging goods within the network is an option in case there is a big difference in sales between the stores. Products are then simply re-distributed with the next delivery* (DC01).
Barriers {186}	
Brand image	*An excessive discounting also has negative effects. The customers' quality perception might suffer when there are 30% off stickers everywhere* (SM03).
Cannibalization effect	*Customers already know our discounting logic. They come into the store, look at the expiration date, wait two days, and then buy the product for the discounted price* (SM02).
Competitive pressure	*Competition plays an important role. It is already extreme in the German market and still getting more difficult. Without competition, we could educate our customers* (SM02).
Data protection regulation	*A project with a digital delivery ticket has failed due to data protection reasons. Data protection is very strong here and a limiting factor* (DC03).
Data quality	*A huge amount of data is already available, but the quality, i.e., the validity of the data, is so far not yet guaranteed* (DC01).
Employee qualifications and motivation	*The onboarding of qualified employees is and will remain a problem. So attempts are made to cover as much as possible with automated systems* (HM01).
Incentive misalignment	*Procurement managers are aiming to buy as cheap as possible, what is often achieved through quantity discounts* (DC04).
Inventory transparency	*Even the most intelligent system is of no use if the information is missing. [...] It would be much easier if customers would withdraw the products following the FEFO principle. [...] In the end, we do not know the expiration dates of products on our shelves* (SM03).
IT integration	*[...] However, a lot of stakeholders have to be involved: suppliers, procurement, POS systems, etc. This is going to be a huge IT project. [...] Our IT systems are not Microsoft or Apple, where you can easily connect other interfaces* (DC03).
Processing costs	*From a process perspective, a two-stage discounting is not beneficial due to high processing costs. [...] A two-stage discounting would have caused an additional cost of x EUR per day and store. This adds up to a significant cost factor* (DC03).
Network density	*Only nearby stores are considered for reallocation. Returning products to the warehouse is mostly too much effort. Logistics costs eat up potential earnings* (DC01).
Food law regulation	*We could do a lot more without the strict regulations. It is really difficult for us, as only food banks are accepted partners. [...] The liability for products given to food sharing is still a limiting factor* (DC04).
Subjectivity of quality	*Quality standards for fruits & vegetables are quite subjective. Decisions are mostly made based on a visual inspection* (DC01).
Supplier dependency	*Adjusting minimum order quantities jointly with the supplier is often a problem. As a small player in the market, you often don't stand a chance here* (SM02).
Impact {67}	
Very high	*Great progress is expected through full automation and algorithms. Everyone is 100% convinced that it will get better, but it is unclear how far it can be pushed* (DC02). *Most successful initiative is the cooperation with food banks, because it simply means saving food from disposal* (OS02).
High	*Another highly important measure is the smart overstock allocation from the warehouses to the stores. [...] This is a big step in the right direction. [...] First results indicate that this is an effective tool* (SM03). *The selection of suitable inbound flows for products is crucial as shelf life is consumed by stock-keeping* (HM02).
Med	*You can control a lot via purchasing modalities, and the subsequent implications are also interesting. The first step is purchasing: here, you could go in the direction of packaging and more precise disposition* (DC03). *How reliable are my suppliers? It happens from time to time that trucks stop at the borders. [...] Weather but also transport routes might cause fluctuations in supply* (DC03).
Low	*Towards the end of the shelf life, the supplier can also only dispose the products* (WS01). *Redistribution of goods is only applicable for selected products. It should not occur in the standard assortment, as cold chain issues might emerge* (DC02).

{ } = Number of codes

Table 3.A2: Coding scheme for data analysis

4 The Impact of Customer Picking on Retail Food Waste – A Data-driven Approach

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Abstract This paper investigates the impact of customer withdrawal behavior in self-service grocery stores on retail food waste. As customer picking for the freshest items leaves products with shorter expiration dates (EDs) on the shelves, both retailers and research see it as a root cause of food waste. However, as currently applied barcodes do not include ED information, insights are so far limited to interviews and simulations. The extent to which retail food waste is caused by customer picking constitutes a research gap. Therefore, we partnered with a leading European grocery retailer to collect missing ED data. We implemented a process adaption in one pilot warehouse and received ED transparency at the batch level, i.e., for each delivery entering a store. Based on a proprietary data set comprising transaction data from 218 outlets and $1,877$ SKUs from the chilled assortment, we develop a novel method to quantify waste caused by customer picking in panel data. Empirical findings show that, on average, 45% of the food waste in our sample is caused by customer picking. Building on the results of the customer picking waste quantification, an exploratory approach is applied to identify product and store-related drivers. We find that the extent of customer picking waste is mainly driven by weekly sales, remaining shelf life, ED variety on the shelf, and the application of ED-based pricing. This study contributes to the understanding of food waste drivers in grocery retail and reveals the connection between customer picking behavior and retail food waste.

4.1 Introduction

Full shelves at any time of the day are a value proposition for grocery retailers. To ensure availability, shelves are frequently replenished before the old inventory is completely depleted (see, e.g., Akkaş and Honhon, 2023). This common retailer's restocking practice leads to multiple expiration dates (EDs) of the same product at the same price on the shelf (see Hansen et al., 2023). Hence, retailers rotate their inventory on the shelf. That means that new inventory is refilled from the back so that first-to-expire items are in front or on top of freshly replenished items (Reiner et al., 2013). As visualized in Figure 4.1, retailers intend the customers to withdraw the foremost and thus oldest item displayed on the shelf.

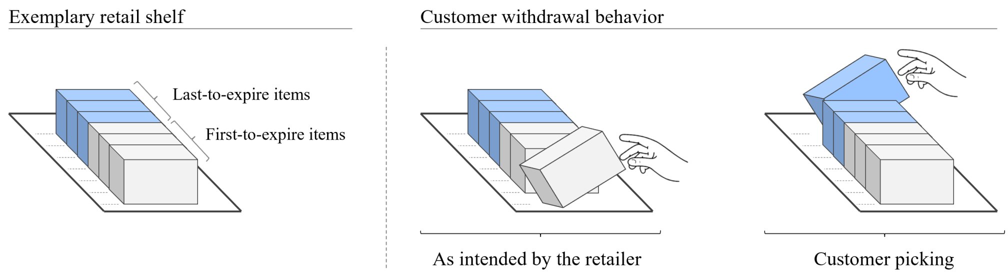

Figure 4.1: Customer withdrawal behavior in grocery retail

However, 81% of customers state to 'always' or 'often' take the ED into account when shopping for groceries (TNS political & social, 2015). Further, consumer studies show a preference for fresh(er) products (see, e.g., Tsiros and Heilman, 2005; Hansen et al., 2023). Knowing about the retailer's replenishment practice, self-service store customers may pick items from the back to obtain products with a more distant ED. Such undesirable withdrawal behavior, denoted as *customer picking* in the following, undermines the retailer's intended withdrawal sequence (see on the right of Figure 4.1). This is problematic as it leaves products with shorter EDs on the shelf. As perishable products have a limited sales period, systematic customer picking increases the risk that the remaining older products will exceed their EDs and convert into food waste over time. At European grocers, the costs associated with food waste almost equal the average profit, i.e., preventing food waste can significantly boost their profit margins (see Klingler et al., 2016; McKinsey, 2023). This makes the identification of the drivers of waste and its management a top priority for retailers (Akkaş and Gaur, 2022). Therefore, this paper investigates the implications of customer withdrawal behavior in grocery retail stores on food waste at the retail stage.

In their research agenda, Akkaş and Gaur (2022) explicitly highlight customer behavior in stores as a promising research field for reducing food waste. In qualitative contributions, opportunistic picking for products with longer EDs is seen as a root cause of food waste at the retail stage (see, e.g., Teller et al., 2018; Winkler et al., 2023a). Yet, quantitative studies that investigate drivers of food waste based on retail data currently neglect the impact of customer picking (see Akkaş et al., 2018). The primary cause of this absence of research is the lack of data offering transparency regarding the ED composition (see Hansen et al., 2023). Therefore, modeling approaches incorporate assumptions on withdrawal behavior to derive implications on food waste (see, e.g., van Donselaar and Broekmeulen, 2012; Tromp et al., 2016; Atan et al., 2023). Only very recent literature investigates customer withdrawal behavior based on field data. While Hansen et al. (2023) and Winkler et al. (2023b) quantify customer picking, they do not link it to waste data. Consequently, the extent to which customer picking causes food waste at the retail stage has not yet been empirically investigated.

We follow an exploratory approach to address this research gap. Our fundamental aim is to explore the impact of customer withdrawal behavior by quantifying the amount of food waste caused by customer picking and to understand store and product-related drivers for this waste. Customer picking only concerns perishable products. We, therefore, focus on perishable products from the chilled assortment, where the ED indicates the remaining shelf life. To identify that food waste is connected with customer picking, it is necessary to trace back what happened in the store from the day of delivery until the day of expiration and the booking as waste. We partnered with a leading European grocery retailer and managed to gain ED visibility in our project for all batches shipped from the warehouse to the stores. This was achieved by introducing an additional data collection step in the operational warehouse processes at one pilot warehouse. Building on this new ED data at the batch level, we explore customer picking waste in a two-step approach. First, we develop a method to classify waste bookings in a panel data set (transactional data on a store-SKU-day level) and quantify the extent to which retail food waste is caused by customer picking. In the second step, we build on these results to identify store and product-related drivers of waste caused by customer picking. We, therefore, leverage complementary master data, divide our sample into the four main product categories, and apply a set of linear cross-sectional estimation models.

The remainder is structured as follows. Section 4.2 analyzes related literature and specifies research gap and questions. In Section 4.3, we outline the research setting and elaborate on the data. Section 4.4 introduces a novel method to estimate food waste caused by customer picking and presents the results for our retail partner. Building on these results, we take an exploratory approach in Section 4.5 to reveal drivers for customer picking waste. Finally, we discuss our contributions to literature and retail practice in Section 4.6.

4.2 Related literature

This section provides an overview of the relevant literature. This serves as a foundation for discussing the research gap and formulating the research questions. We build on two literature streams: (i) modeling approaches simulating the implications of customer withdrawal behavior on retail food waste and (ii) empirical literature quantifying customer picking in retail stores.

(i) Modeling approaches simulating the implications on food waste

Customer withdrawal behavior has been integrated into modeling approaches in the field of grocery retailing. By reviewing food waste-related planning problems in grocery store operations, Riesenegger et al. (2023) show that, especially in replenishment literature, customer withdrawal is an established input factor. Some contributions track food waste in dependence of customer withdrawal behavior, often considered as specific ratios for LEFO and FEFO customers. For example, van Donselaar and Broekmeulen (2012) combine stochastic modeling, simulation, and regression analysis to calculate the anticipated quantity of food waste within an inventory system. Initially, they approximate food waste based on a strict FEFO withdrawal policy and then extend their findings based on simulation experiments. They demonstrate that by transitioning to a LEFO withdrawal policy while keeping all other factors unchanged, the food waste ratio increases nearly threefold, rising from 9% to 26%. Tromp et al. (2016) present a simulation model to assess the impact of different interventions on food waste. Simulation results show that customer picking causes food waste in grocery outlets. Specifically, a 10% decrease in the share of LEFO customers (from 0.45 to 0.405) is associated with a 14% decrease in food waste. Broekmeulen and van Donselaar (2019b) investigate options to improve inventory replenishment when the visibility of EDs is restricted. The authors use discrete event simulation to evaluate the performance of inventory systems for varying degrees of ED visibility (i.e., visibility at the item level, visibility at the batch level, and no visibility). The estimate of waste increases with the fraction of LEFO customers. The simulation results reveal that total costs for retailers are very similar between ED visibility at the batch level and ED visibility at the item level. Furthermore, a method to estimate the withdrawal behavior based on sales, waste, and inventory data is presented. Further, Buismann et al. (2020) explore a dynamic pricing strategy, factoring in a stochastic demand distribution between LEFO and FEFO customers. They assume that the share of LEFO customers migrating to FEFO corresponds directly to the magnitude of the discount offered and quantify waste ratios for different scenarios based on this assumption. They show that in the absence of discounts, food waste rates are up to five times higher in the 100% LEFO scenario and that discounts mitigate the impact of customer picking on retail food waste. In line with van Donselaar and Broekmeulen (2012) and Tromp et al. (2016), the authors constitute customer withdrawal behavior as a driver for retail food waste and recommend further investigation in retail practice. Finally, Atan et al. (2023) explore the effects of displaying and discounting perishable products on retail profits and waste. The authors develop an infinite-horizon, periodic-review model for managing the inventory of a deteriorating product with a finite shelf life. They distinguish between passive and active consumers following the classification of Winkler et al. (2023b). Passive consumers tend to purchase easily accessible units if they provide positive utility, while active consumers seek out the unit with the highest positive utility regardless of its accessibility. The results show that the share of active consumers influences retail waste depending on the display setting. If the old batch is in front (layered with the fresh batch in the back), a higher share of active consumers increases retail waste.

(ii) Empirical literature quantifying customer picking Very recent literature collects data in the field. Hansen et al. (2023) conduct a field study and collect transaction line, inventory, and shelf price panel data. The scope of the analysis is the impact of shelf organization and dynamic discounting on consumer choice, investigated in one product group (fresh meat). Results show that consumers pick a fresher item in approximately 50% of all purchases, and they have a preference for freshness and discounts. Actual waste numbers are not recorded. Based on the insights from the field, they estimate a discrete choice model to approximate the impact of customer withdrawal behavior on retail waste. They consider different retailer settings in shelf organization and discounting to conduct counterfactual simulations. The results suggest that implementing stock rotation can lead to an 8% reduction in food waste while offering discounts can result in a 13% reduction. Combining both policies leads to an expected food waste reduction of 31%. Lastly, Winkler et al. (2023b) collect ED data manually by periodic stocktaking for 42 products in six grocery stores. They quantify the extent of undesirable customer picking, on average, over 14 product groups, in a range between 26% and 35%. They further outline the retail setting and investigate options within the retailer's sphere of influence that might impact customer picking. Results indicate that increasing the search effort with shelf allocation and layout planning, maximizing the remaining shelf life, and limiting the ED variety on the shelf are options to mitigate customer picking proactively.

Summary, research gap and question The two literature streams reviewed above provide evidence that customer withdrawal behavior is connected to retail food waste. Modeling approaches in stream (i) leverage the withdrawal behavior as an input factor to demand and inventory models. As the empirical foundation for customer picking in retail stores was long time missing, they rely on assumptions for specific ratios for LEFO and FEFO customers. Results indicate that FEFO customers may cause a substantial share of retail food waste. Broekmeulen and van Donselaar (2019b) are the first to present a method to estimate withdrawal behavior based on sales, waste, and inventory data. However, they do not answer the question of to what extent food waste in grocery retail is caused by customer picking. All contributions in this stream are missing the empirical data to move from simulation to actual quantification of retail food waste. Recent empirical literature in stream (ii) moves toward quantifying customer picking. The findings provide the missing empirical foundation for modeling approaches and reveal options within the retailer's sphere of influence to mitigate customer picking. However, the link to empirical retail waste data is not established.

To summarize, even though pertinent literature provides model-based evidence of withdrawal behavior as food waste driver, the extent to which customer picking causes food waste at the retail stage has not yet been empirically investigated. Consequently, as the empirical foundation is missing, an investigation into the potential store and product-related drivers of food waste caused by customer picking is also missing. While Hansen et al.

(2023) and Winkler et al. (2023b) investigate options to mitigate customer picking, store and product-related drivers of waste caused by customer picking have not yet been investigated. The differentiation between drivers of customer picking and drivers of retail food waste caused by customer picking is crucial, as not every customer picking necessarily leads to retail food waste. This study, therefore, explores the following two associated research questions (RQs):

RQ1 *To what extent does customer picking for EDs cause food waste in grocery retail?*

RQ2 *What are store and product-related drivers of food waste caused by customer picking?*

4.3 Research setting and data

We partnered with a leading European grocery retailer, which we refer to as our partner retailer in the following. We first describe the empirical setting in Section 4.3.1, and outline the data collection and preparation in Section 4.3.2.

4.3.1 Empirical Setting

The following provides background on our partner retailer, defines the product scope of this study, and reviews current store operations.

Background on our partner retailer Our retail partner is a multi-billion Euro grocery retailer operating a network of over 3,500 stores throughout Europe. The assortment is typical for a full-range retailer and consists of more than 50,000 items across several categories, such as ambient, fruits & vegetables, chilled, frozen, and non-food products. The vast majority of perishable products are distributed to stores through regional warehouses operated by the retailer. Store orders are placed by the retailer's automated forecasting and replenishment system. The system calculates daily orders for each SKU (stock keeping unit) by taking into account various factors like the current stock levels, shelf capacities, and demand forecasts. While store managers have the authorization to adjust these orders, such interventions are relatively rare. The orders are subsequently processed in the warehouse network. Each store is allocated to one and only one dedicated regional warehouse and is delivered daily.

Product scope The study scope was aligned with the retailer's senior management. Customer picking for EDs is suspected to be a major driver for food waste at stores. Retail food waste due to product expiration only concerns perishable products. Within the range of perishable products, we focus on CPG products from the chilled assortment for three reasons. First, those products have a fixed shelf life and carry ED labels. The labels provide guidance on the freshness and safety of a product indicated by a "use by" or "best before" date. The type of label and the ED are determined by the manufacturer. Second, CPG products are standardized, and the ED is the only objective differentiating feature for customers. In categories not carrying ED labels, such as fruits & vegetables, the customer's choice is prone to a subjective quality assessment, which is not in the scope of our study. Third, chilled products have the shortest shelf life compared to the ambient and frozen categories. This makes the product category more complex for a retailer and more attractive for the customers to pick the freshest item on the shelf. The retailer confirmed that this category has the highest relevance for our study as products are especially prone to the risk of expiration. Besides fruits & vegetables, chilled products have by far the highest waste rates at the retailer.

Store operations We conducted multiple field visits to warehouses and stores to gain a deeper understanding of the retailer's operations. On-site, we observed the processes and the flow of products from inbound logistics to the shelf. In particular, we focused on replenishment practices and interviewed store employees to understand each process step in detail. For the chilled assortment, stores are delivered daily by the regional warehouse. Upon arrival at the store, deliveries are handled in one of two ways: They are either directly restocked onto the dedicated shelves (if labor capacity and shelf space allow) or temporarily placed in backroom storage for later replenishment. Due to limited storage space in backrooms, particularly for chilled products, items are transferred to the shelves as soon as labor capacity is available. Usually, dedicated employees are responsible for the chilled assortment in the store. The daily shelf replenishment involves refilling fresh inventory and rearranging products to adhere to the desired FEFO arrangement. That means that older items are placed at the front while fresh ones are replenished from the back. The employees check the shelf arrangement multiple times a day and reorganize the shelf in case customers have rummaged on the shelf. Further, employees are responsible for regularly checking inventory levels to ensure inventory accuracy and screen the shelves for product expiration. When an item passes the ED, it becomes unsalable for a retailer. The retailer has corporate "Expiration Date Guidelines" in place that require products to be removed from the shelves in a range from up to two days prior to the ED until the early morning of the day after the ED. As products are often sold until the closing of business on the date of expiration, they can also be removed from the shelves the next morning before opening. Store employees must prioritize removing those items from the shelves as their first task in the morning. When store employees remove soon-to-expire items from the shelves, the shelf removal is directly recorded as 'spoilage' in the inventory system, and the items are collected in waste bins for disposal. The retailer distinguishes between three types of food loss in their inventory system: 'theft', 'breakage', and 'spoilage'. Further root causes, i.e., why an item has passed the ED or why it was damaged, are not systematically recorded. In the following, we will focus on food waste recorded as 'spoilage' as this is the only loss connected to the ED. To prevent food waste, store managers can decide to stimulate demand for soon-to-expire items with a simple one-time discount of 30%. This is a decentralized decision within the store manager's responsibility. Discounted items are marked with a "*30% off*" sticker, and the discount is deducted at the cash desk.

4.3.2 Data collection and description

After outlining the retail setting, this section first highlights the issue with currently applied identification codes and then details our approach for data collection. It concludes by describing the data received from our partner retailer.

Identification codes Our partner retailer follows the international GS1 standards in supply chain and logistic management. For our context, we need to distinguish between two different identification codes applied at different levels of packaging: the Serial Shipping Container Code (SSCC) and the Global Trade Item Number (GTIN) (see GS1, 2019). The SSCC is used at the warehousing stage for tracking the movement of goods. In our context, the SSCC provides a unique number for every delivery arriving at one of the retailer's warehouses. The GTIN is a unique identifier for trade items. The number and the barcode are the consumer-visible on-pack information printed on every item. The GTIN assigned to an item is consistent over time and for all units of this item. The GTIN is used for product identification at the cash desk, pricing, and inventory management. Neither the SSCC nor the GTIN include ED information. Hence, ED data was not systematically collected, and our partner retailer lacked information on the inventory composition with regard to available EDs at the warehousing stage and on the shelves at the stores.

Collecting ED data To overcome the existing information gap, we needed to record ED data at some point in the retail internal supply chain (ranging from inbound logistics to the shelf). Jointly with the retailer, we decided to adapt the process at the warehousing stage as it was more efficient than collecting ED data in each store separately. We came up with the following process adaption:

(1) For every delivery entering the warehouse, ED information is collected by warehouse employees and linked to the SSCC (batch-identifier) in the IT system – this is feasible as all items in a logistic unit stem from the same production batch and have an identical ED.

(2) When orders are picked for distribution to stores, warehouse employees again scan the SSCC of the pallet from which the products were removed.

(3) Once the order is shipped to the store, the ED linked to the SSCC is then linked to the store shipment in the backend of the IT system.

As a result of this process adaption, we gained ED information for every delivery shipped to a store from the warehouse. As this data collection constitutes an increasing effort for warehousing employees, we agreed with the retailer to adapt the process in one pilot warehouse. The pilot warehouse was selected based on relevance (in terms of associated stores) and available labor capacity. We ensured that the pilot was representative regarding size and operations for the other warehouses in the network. The warehouse selected supplies 218 stores in one region of Germany. Training of employees and initial testing took place in March/April 2021. The process adaption (data collection period) lasted nine months, from May 2021 to January 2022.

Data description After the data collection period, we obtained a proprietary panel data set comprising all SKUs in our product scope. Each SKU listed by the retailer in the chilled assortment can be described by one of four product categories (i.e., cheese, convenience, delicacies, or milk/dairy). The granularity of the data received is on store-SKU-day level, i.e., we observe information about inventory level, units sold, price per unit, delivery quantity, spoilage booking, and other inventory changing interventions (e.g., theft or breakage) for each SKU in each store for every single day over the data collection period. Based on the aforementioned process adaption, we were able to match ED information to store shipments on a store-SKU-day level. That means we know the ED and the delivery date for each product batch entering a store. Based on the delta of ED and delivery date, we can compute the remaining shelf life of a product. The initial data set consists of over 88 million records, each presenting a daily inventory position of a store-SKU combination. We exclude some records to avoid data gaps and ensure data consistency. The following exclusion criteria were applied on different levels:

- *Store-SKU-level*: We consider only store-SKU combinations with an average remaining shelf life of 56 days or less upon arrival at the store (denoted as *Cap56* in the following). The Cap56 accounts for the perishability of products and ensures that we observe at least five deliveries throughout our data collection period of nine months (9 months ÷ 56 days).
- *Store-level*: We restrict our data set to stores opened the entire time over the course of the data collection period to avoid ramp-up or ramp-down effects.
- *SKU-level*: We exclude SKUs sold in less than twenty stores to avoid biases based on regional limited offerings.

The final sample represents 211 stores and 1,877 SKUs. Summary statistics of the dataset are presented in Table 4.1. We see differences in the size of the product categories, the remaining shelf lives, the retail price, and the waste ratios. The remaining shelf life when products enter the store varies across all categories. The chilled assortment comprises highly perishable products (e.g., fresh milk with seven days) and more shelf-stable products capped at a maximum of 56 days remaining shelf life (e.g., curd). On average, 5.46%

of all products are wasted because of spoilage and an additional 0.18% because of breakage.

	Cheese	Convenience	Delicacies	Milk/Dairy	All
Number of SKUs	258	164	702	753	**1,877**
Mean RSL, in days	33	34	26	27	**28**
Min. RSL, in days	8	6	5	6	**5**
Max. RSL, in days	56	56	56	56	**56**
Mean price, in EUR	2.10	2.01	2.40	1.32	**1.85**
Mean spoilage ratio	3.61%	5.45%	7.14%	4.71%	**5.46%**
Mean breakage ratio	0.11%	0.13%	0.18%	0.22%	**0.18%**

Table 4.1: Summary statistics for all product categories in the chilled assortment (Cap56)

Further, our partner retailer provided us with additional master data for stores and products. On an SKU level, we obtained descriptive and identifying information, including SKU category, retail price, branding (binary variable), organic (binary variable), and required shelf life at the warehousing stage. On a store level, we received descriptive information, including store size, location, opening year, opening hours, and average basket size.

4.4 Customer picking waste quantification

In this section, we present a novel method to estimate food waste caused by customer picking from panel data when ED information for each delivery on batch level is available (Section 4.4.1) and conclude by presenting our results on customer picking waste quantification (Section 4.4.2).

4.4.1 Method for customer picking waste identification

To investigate if food waste is connected with customer picking, it is necessary to trace back what happened in the store from the day of delivery until the day of product expiration. We consider a single perishable item i in a store s with a fixed ED to explain the method for customer picking waste identification. For the sake of clarity, we simplify by omitting the indices i and s. Table 4.2 summarizes the notation.

Symbol	Description
T	Set of days (sales period), $T = \{j, \dots, j + M_j + r_j^+\}$
J	Set of delivery days $J \subseteq T$
M_j	Remaining shelf life of delivered items at delivery day j
D_j	Quantity of delivered items at delivery day j
I_t	Inventory on hand at the end of day t
S_t	Sales at day t
W_t	Waste due to expiration at day t
W_j^{CP}	Picking waste originating from the batch delivered at day j
B_t	Other waste or inventory changes at day t
r_j^- (r_j^+)	Range of days t before (after) the expiration date of delivery j to be investigated for waste bookings
x_{j_0}	Delta between the initial inventory I_{j_0} and the inventory outflow

Table 4.2: Notation for a single perishable item i in store s

As a result of the process adaption described in Section 4.3, we know the ED from which the remaining shelf life M_j can be derived for each delivery entering a store at delivery day j, i.e., ED$= j + M_j$. Figure 4.2 illustrates an exemplary panel data snapshot we leverage to explain the three conditions we propose to investigate if a waste booking W_t at a point in time t in the considered sales period can be classified as caused by customer picking. At j_0, a new delivery with D_{j_0} units enters the store, leading to a total end of day inventory of I_{j_0}. Those newly delivered items have a remaining shelf life of M_{j_0}. In the upcoming days, we observe sales S_t, other waste or inventory changes B_t, and waste due to expiration W_t that depart from the inventory I_{j_0}. The new delivery at j_1 refills the inventory to I_{j_1}. Until the ED $j_0 + M_{j_0}$, we again observe sales S_t and waste W_t due to expiration. To declare that a waste booking W_t can be fully or partially classified as picking waste $W_{j_0}^{CP}$, we need to verify the following three conditions.

(1) Delivery matching: The delivery day j_0 marks the starting point of the considered sales period T. We search in our panel data for a waste booking recorded within a range of days before $r_{j_0}^-$ and after $r_{j_0}^+$ the ED $j_0 + M_{j_0}$ of the batch delivered at j_0. If we find a waste booking in this time frame, we assign the waste booking W_t to a delivery at day j_0. W_{j_0} is defined as follows:

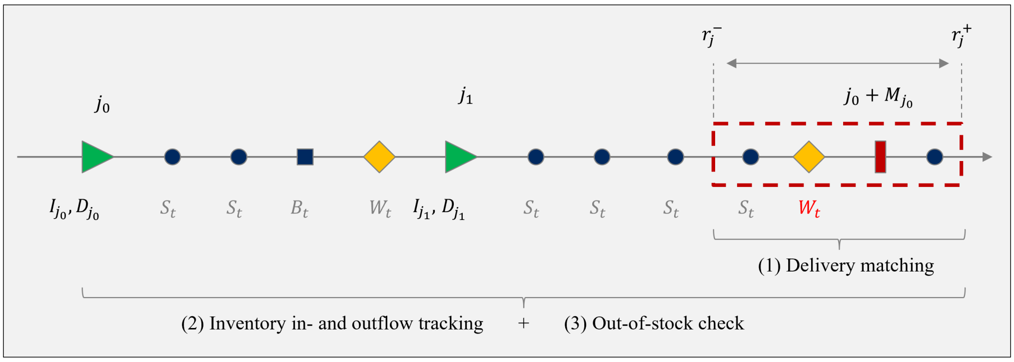

Figure 4.2: Simplified conditions for customer picking waste identification for item i in store s (visualization in line with Dietrich (2023))

$$W_{j_0} = \sum_{t=j_0+M_{j_0}-r_{j_0}^-}^{j_0+M_{j_0}+r_{j_0}^+} W_t \tag{4.1}$$

Due to the retailer's "Expiration Date Guidelines", we cannot determine a single day around the ED on which we would always expect the waste booking. Hence, a more flexible approach (i.e., a range) is required to connect waste bookings and deliveries. Further, a range is also beneficial in our setting as shelf removals and waste bookings are manual tasks conducted by store employees, and store processes are subject to variations between but also within stores.

(2) Inventory in- and outflow tracking: Next, we compute the variable x_{j_0} denoted as the delta between the initial inventory I_{j_0} and the inventory outflow. To calculate the inventory outflow, we sum up sales S_t and other waste or inventory changes B_t (e.g., theft or breakage) for $t = \{j_0+1, \ldots, j_0+M_{j_0} + r_j^+\}$ and waste bookings W_t for $t = \{j_0 + 1, \ldots, j_0 + M_{j_0} - r_j^-\}$. This results in the following equation:

$$x_{j_0} = I_{j_0} - \left(\sum_{t=j_0+1}^{j_0+M_{j_0}+r^{+}_{j_0}} S_t + B_t + \sum_{t=j_0+1}^{j_0+M_{j_0}-r^{-}_{j_0}} W_t \right) \tag{4.2}$$

In case $x_{j_0} \leq 0$, we can assume that the realized demand would have been high enough to sell off the entire inventory at hand I_{j_0}.

(3) Out-of-stock check: With the last condition, we check if the initial inventory I_{j_0} was completely sold before W_{j_0} occurred. In case we identify a stock-out situation before W_{j_0}, this undermines condition (1), and we cannot longer assume that a waste booking W_t stems from the delivery at j_0.

$$I_t > 0 \qquad \forall t \in T \tag{4.3}$$

Based on the values for W_{j_0} and x_{j_0}, and the out-of-stock check, we distinguish between two cases to quantify customer picking waste $W^{CP}_{j_0}$. Table 4.3 visualizes the waste classification logic.

Case		Waste W_{j_0}	Delta x_{j_0}	OOS check[1]	Customer Picking waste $W^{CP}_{j_0}$
(i)	Waste booking and sufficient demand	> 0	≤ 0	✓	W_{j_0}
(ii)	Waste booking and demand shortage	> 0	> 0	✓	$\max\{W_{j_0} - x_{j_0}, 0\}$

[1] OOS = Out-of-stock

Table 4.3: Waste classification logic (in line with Dietrich (2023))

In the first case (i), we can allocate a waste booking W_{j_0} to the delivery day j_0, i.e., $W_{j_0} > 0$. At the same time, the sum of inventory outflows (see also Equation (4.2)) is equal or higher than the initial inventory I_{j_0}, i.e., $x_{j_0} \leq 0$, and no out-of-stock situation occurred. Under these circumstances, we would not expect a waste booking. The inventory I_{j_0} should have been completely sold until $j_0 + M_{j_0} + r_j^+$ when customers stick to the retailer's intended FEFO withdrawal sequence. However, as we see a waste W_{j_0}, we can assume that the FEFO withdrawal sequence was violated and classify this waste as caused by customer picking. In the second case (ii), we can again allocate a waste booking to a delivery, and no out-of-stock situation occurred. However, the sum of inventory outflows is smaller than the initial inventory I_{j_0}, i.e., $x_{j_0} > 0$. In this case, the waste booking is expected as realized demand was not high enough to sell off all items in time. However, also in this situation, waste caused by customer picking can occur. If $W_{j_0} > x_{j_0}$, we can again assume that the retailer intended FEFO withdrawal sequence was violated and classify $\max\{W_{j_0} - x_{j_0}, 0\}$ as customer picking waste.

Based on this classification, we can calculate the waste caused by customer picking for each delivery. The total waste caused by customer picking is denoted as $\mathrm{W}_{j_0}^{CP}$ and calculated with Equation (4.4). To quantify the share of food waste caused by customer picking, we calculate the *waste ratio customer picking* denoted as $\mathrm{WRCP}_{i,s}$ with Equation (4.5).

$$\mathrm{W}_{j_0}^{CP} = \begin{cases} \max\left\{W_{j_0} - \max\{x_{j_0}, 0\}, 0\right\} & \text{if } I_t > 0 \ \forall t \in T \\ 0 & \text{otherwise} \end{cases} \tag{4.4}$$

$$\mathrm{WRCP}_{i,s} = \frac{\sum_{j \in J} \mathrm{W}_j^{CP}}{\sum_{t \in T} W_t} \tag{4.5}$$

To avoid double counting of waste bookings for two or more deliveries, the used algorithm assigns each inventory outflow quantity to a specific delivery, starting with the earliest delivery dates. This meticulous allocation process guarantees that the sum of outflows for each delivery aligns with the delivery quantity. Any remaining unassigned products are correctly tracked for subsequent calculations, ensuring an accurate representation of waste.

To ensure accurate tracking of waste quantities and maintain data transparency, a warm-up phase is introduced at the start of calculations (see also Dietrich, 2023). During this period, deliveries and corresponding waste bookings are excluded from consideration until full transparency is achieved, typically when the first delivery with complete expiration date information expires. This approach aligns with the FEFO delivery principle, preventing the counting of deliveries and waste during the warm-up period. Conversely, a cool-down phase is implemented at the end of the data set to account for deliveries with expiration dates extending beyond the observed time frame. During this phase, inventory changes, including waste bookings, are only included up to the last expiration date within the observed period, excluding those occurring afterward. These warm-up and cool-down periods are crucial for maintaining data integrity and ensuring precise waste calculations.

4.4.2 Results on customer picking waste quantification

We only present results for those item-store combinations (referred to as observations in the following) with at least one waste booking within the data collection period. 96% of all investigated items ($1,809$ of $1,877$) have at least one waste booking (in at least one store) within the data collection period. Based on the corporate guidelines and validations during field visits, we determine the range for removing close to expired or expired items with four days: two days prior to ($r_j^- = 2$) and one day after ($r_j^+ = 1$) the ED (see also Section 4.3.1). Table 4.4 summarizes our results on the customer picking waste quantification for $133,911$ observations from $1,809$ items and 211 stores. Customer picking causes waste in all investigated categories, with an average waste share of 45%. The product category with the highest WRCP is Milk/Dairy with, on average, 49%. Similar results can be observed for the Cheese (47%) and Delicacies (43%) category. The Convenience category has by far the lowest WRCP with, on average, 28%. This category comprises products that are intended for direct consumption, e.g., fresh smoothies, juices, ready-to-eat sandwiches, and salads. Results indicate that the customer's intention of when to consume a product affects their withdrawal behavior. Further, results indicate not only a difference between but also within product categories. Consistent across all categories, we see extreme values of 0% and 100% WRCP for at least one item-store combination.

		Cheese	Convenience	Delicacies	Milk/Dairy	**All**
$\text{WRCP}_{i,s}$	mean	0.47	0.28	0.43	0.49	**0.45**
	median	0.43	0.00	0.33	0.50	**0.40**
	max	1.00	1.00	1.00	1.00	**1.00**
	min	0.00	0.00	0.00	0.00	**0.00**
	s.d.	0.41	0.39	0.38	0.39	**0.39**
Number of items		242	150	683	734	**1,809**
Observations		13,968	7,926	44,835	67,182	**133,911**

Table 4.4: Results on the customer picking waste quantification

Figure 4.3 presents the store and item level breakdown of our results. We see that customer picking waste occurs in all stores in our sample, but the extent varies. The WRCP on a store level ranges from a minimum of 18% to a maximum of 62%. Almost half of the investigated stores (104 from 211) show a WRCP between 40% and 50%. At the item level, we see a larger WRCP variation. While for 13% (92 + 142) of the products, the WRCP lies below 20%, we also observe 4% (41 + 18 + 7) of the products with a WRCP of more than 70%. The average remaining shelf life of the top 10% of products with the highest WRCP is 22 days, compared to 31 days for the 10% of products with the lowest WRCP. To summarize, we can conclude that customer picking is a root cause of food waste at the retail stage. As the WRCP is substantial in magnitude, it is crucial for retailers to understand store and product-related drivers. Therefore, we leverage our results as a foundation and continue identifying the WRCP drivers.

Figure 4.3: Distribution of the WRCP across stores and items

Even though this paper focuses primarily on customer picking waste quantification, the method developed in Section 4.4.1 allows us to draw conclusions regarding the amount of over-ordering waste, i.e., the waste that occurs in case the quantity delivered can not be sold until the day of expiration (i.e., the demand is not high enough to sell off all items in time). A waste booking is classified as over-ordering if we can allocate it to a delivery, no out-of-stock situation occurs, the sum of inventory outflows is smaller than the initial inventory I_{j_0}, and no customer picking waste is detected. The mean over-ordering waste ratio for all product categories is 24%. In case a waste booking does not fall in any of the delivery matching time periods (-2,-1, ED, +1), we cannot classify it into customer picking or over-ordering waste. Therefore, the remaining 31% $(= 1-(0.45+0.24))$ of waste bookings remain unclassified by our method.

4.5 Customer picking waste driver identification

We take an exploratory approach to identify the drivers for customer picking waste. Section 4.5.1 introduces the variables considered. The cross-sectional estimation models, estimation results, and robustness checks are presented in Section 4.5.2.

4.5.1 Data selection and description

Variables for analysis In addition to the characteristics for an item-store combination (e.g., remaining shelf life for item i in store s) derived from the panel data, we leverage the master data for item and store characteristics (see also Section 4.3.2) to investigate potential drivers for customer picking waste. In the first step, we match the results from Section 4.4 with all available information to a combined cross-sectional data set, referred to as 'conditional data set' in the following. Next, we address the concern of multicollinearity (see, e.g., Guyon and Elisseeff, 2003) and calculate the Pearson correlation coefficients (PCC) for all possible combinations of features. We identify pairs with both strong positive and strong negative correlations (PCC $>\mid 0.5 \mid$), and for each of these pairs, we select only one variable as input for our cross-sectional estimation model (Shieh and Fouladi, 2003). Table 4.5 summarizes the final set of variables considered.

The target variable $\text{WRCP}_{i,s}$ is the outcome of the picking waste quantification in Section 4.4 and is defined as the share of food waste caused by customer picking for an item i in store s. The variables derived from the panel data analysis are calculated as average values over the course of our data collection period. $\text{WeeklySales}_{i,s}$ represents the average number of units sold per week for item i in store s. $\text{RSL}_{i,s}$ defines the average remain-

Variable	Type	Description
Target variable		
$\text{WRCP}_{i,s}$	Dep.	Share of food waste caused by customer picking for an item i in store s
Predictor variables		
$\text{WeeklySales}_{i,s}$	Indep.	Average number of units sold per week for item i in store s
$\text{RSL}_{i,s}$	Indep.	Average remaining shelf life at the day of delivery for item i in store s
$\text{EDVariety}_{i,s}$	Indep.	Estimated average expiration date variety for item i in store s
$\text{EDPricing}_{i,s}$	Indep.	Average ED-based price discount in Euro for item i in store s
RetailPrice_{i}	Indep.	Retail price of item i in Euro
Organic_{i}	Indep.	Binary variable; indicating whether item i is labeled as a organic product or not
SalesArea_{s}	Con.	Sales area of store s in square meter
UrbanLocation_{s}	Con.	Binary variable; indicating whether store s is located in an urban area or not

Table 4.5: Overview of variables

ing shelf life at the day of delivery for item i in store s. The $\text{EDVariety}_{i,s}$ represents a proxy for the estimated ED variety, i.e., the number of different expiration dates on the shelf. We can assume that all units delivered in one batch have an identical ED as the delivery comprises products from the same production batch. As perishable products are replenished frequently, we assume that the store receives a new ED with every new delivery entering the store. We validated this assumption in the panel data, showing that in 95% of deliveries, the ED has changed compared to the previous delivery. Therefore, we define the $\text{EDVariety}_{i,s}$ as the average end of day inventory divided by the average delivery quantity for item i in store s. Further, we leverage the $\text{EDPricing}_{i,s}$ as a proxy for the effect of discounts on soon-to-expire items on customer picking waste. The partner retailer has two promotional activities that lead to a deviation from the retail price. First, the centrally planned price promotions, which take effect in all stores at the same time in our sample region. Second, the decentralized option to stimulate demand by expiration-date-based pricing of overstocks. Discounting of overstocks is within the store manager's responsibility. They are allowed to discount soon-to-expire items two days before product expiration with a simple one-time discount of 30% to prevent food waste. $\text{EDPricing}_{i,s}$ captures the average ED-based discount in EUR for item i in store s. The variable is calculated as the delta between the average price after centrally planned price promotions and the average store-specific price observed throughout our data collection period. The remaining item and store-specific variables are self-explanatory and defined in detail in Table 4.5. We define the store-specific variables as control variables as they describe strategic long-term decisions with limited scope for intervention by the retailer.

Descriptive statistics and variable transformation Table 4.6 presents descriptive statistics and the correlation matrix for the conditional data set (before variable transformation). The data set comprises $133,911$ item-store level observations across $1,809$ items and 211 stores. Analysis of the raw data suggests a nonlinear relationship between the target variable (WRCP) and some of the predictor variables. Further, we see variables with a wide spread, i.e., they have a large standard deviation compared to their mean. Therefore, prior to fitting our model, we log transform the variables WeeklySales and EDPricing to induce normality, limit the impacts of outliers, and simplify the interpretation (see Afifi and Clark, 1996; Wooldridge, 2013). Further, we divide the SalesArea variable by a factor of 100. This adjustment is necessary as the variable can take on large values that lead to very small coefficients in parameter estimation.

Variable		mean	max	min	s.d.	1.	2.	3.	4.	5.	6.	7.	8.	9.
1.	WRCP	0.45	1.00	0.00	0.39	–								
2.	WeeklySales	10.27	720.91	0.03	19.11	0.20^a	–							
3.	RSL	25.64	56.00	4.67	8.22	-0.10^a	-0.09^a	–						
4.	EDVariety	0.94	10.69	0.02	0.31	0.10^a	0.14^a	0.04^a	–					
5.	EDPricing	0.07	0.86	0.00	0.05	-0.03^a	0.01^a	-0.05^a	-0.02^a	–				
6.	RetailPrice	1.97	11.90	0.15	0.99	-0.10^a	-0.24^a	0.02^a	-0.04^a	0.30^a	–			
7.	Organic	0.12	1.00	0.00	0.32	0.04^a	0.01^a	-0.04^a	0.01^a	-0.08^a	-0.05^a	–		
8.	SalesArea	1,458	8,828	328	908	0.03^a	0.08^a	-0.02^a	0.02^a	0.11^a	0.02^a	0.00	–	
9.	UrbanLocation	0.52	1.00	0.00	0.50	0.03^a	0.03^a	-0.01^c	0.05^a	-0.07^a	0.02^a	0.00	-0.10^a	–

^{a} $p < 0.001$; ^{b} $p < 0.01$; ^{c} $p < 0.05$. $n = 133,911$ across $1,809$ items and 211 stores.

Table 4.6: Descriptive statistics and correlation matrix for the conditional data set

4.5.2 Model description and results

Model development To identify drivers for customer picking waste, we apply an Ordinary Least Squares (OLS) regression on our cross-sectional data. The OLS regression is a well-established approach for driver identification as the impact of individual predictors on the target variable in terms of the magnitude and direction can be easily interpreted (see, e.g., Wooldridge, 2013). Similar to the approach in Section 4.4, we split our conditional data set following the product category split into four sub-samples. We then apply the model defined in Equation (4.6) on the four sub-samples (denoted with the category name) and the entire conditional data set (denoted with 'All categories').

$$\begin{aligned} E(\mathrm{WRCP}_{i,s}) = {} & \beta_0 + \beta_1 \cdot \mathrm{WeeklySales}_{i,s} + \beta_2 \cdot \mathrm{RSL}_{i,s} + \beta_3 \cdot \mathrm{EDVariety}_{i,s} \\ & + \beta_4 \cdot \mathrm{EDPricing}_{i,s} + \beta_5 \cdot \mathrm{RetailPrice}_i + \beta_6 \cdot \mathrm{Organic}_i \\ & + \beta_7 \cdot \mathrm{SalesArea}_s + \beta_8 \cdot \mathrm{UrbanLocation}_s + \epsilon \end{aligned} \tag{4.6}$$

β_0 is the intercept, $\beta_1, ..., \beta_8$ are the regression coefficients associated with the predictor variables, and ϵ is the error term, accounting for unexplained variance in the model. Standard errors are clustered at the store level.

Estimation results Table 4.7 presents the results for our cross-sectional estimation models. On an aggregated level, we find significant effects for all independent variables considered in our analysis (see Table 4.7 column 'All categories'). Effect size and significance level vary for some variables between product categories, but the effects are directionally consistent (see Table 4.7 columns 'Cheese' to 'Milk/Dairy'). Considering the R^2 values, between 14.7% and 17.6% of the variation in the WRCP is explained by the chosen predictors.

	Cheese		Convenience		Delicacies		Milk/Dairy		All categories	
Variables	**Est.**	**SE**	**Est.**	**SE**	**Est.**	**SE**	**Est.**	**SE**	**Est.**	**SE**
(Intercept)	0.358	0.019***	0.366	0.024***	0.243	0.011***	0.299	0.015***	0.290	0.011***
WeeklySales	0.108	0.003***	0.108	0.004***	0.114	0.002***	0.111	0.002***	0.110	0.001***
RSL	-0.005	0.000***	-0.005	0.000***	-0.002	0.000***	-0.005	0.000***	-0.004	0.000***
EDVariety	0.074	0.013***	0.047	0.013***	0.062	0.008***	0.047	0.009***	0.061	0.006***
EDPricing	-0.191	0.037***	-0.321	0.077***	-0.145	0.021***	-0.287	0.020***	-0.209	0.014***
RetailPrice	0.006	0.004	0.004	0.007	0.023	0.002***	0.047	0.003***	0.027	0.002***
Organic	0.013	0.013	-0.005	0.069	0.013	0.006*	0.026	0.004***	0.024	0.003***
Controls	✓		✓		✓		✓		✓	
R^2	0.176		0.147		0.166		0.154		0.172	
$Adj.R^2$	0.175		0.146		0.166		0.154		0.172	
Observations	13,968		7,926		44,835		67,182		133,911	

Note: *p<0.05; **p<0.01; ***p<0.001; Standard errors (SE) are clustered on a store level.

Table 4.7: Cross-sectional estimation model results (OLS)

For interpretation of the results, we have to recall that the variables WeeklySales and EDPricing were log transformed prior to fitting the models. The coefficients of those variables can be interpreted in terms of percent change (see Wooldridge, 2013). *WeeklySales* demonstrates a significant positive association with the WRCP across all categories, suggesting that customer picking is a greater problem for products with high sales volumes. Thus, we can say that for a 10% increase in weekly sales, the WRCP increases by $\beta_1 \times log(1.1) = 0.011$, which equals 1.1 percentage points (pp.) for Milk/Dairy and Delicacies and 1.0 pp. for Cheese and Convenience products. *EDPricing* shows a significant negative impact on the WRCP across all categories. This implies that the WRCP decreases with the application of ED-based pricing in the store. For a 10% increase in EDPricing, the WRCP decreases by at least $\beta_4 \times log(1.1) = 0.014$, which equals 1.4 pp. in the Delicacies category to a maximum of 3.1 pp. in the Convenience category.

The standard interpretation of a linear regression analysis can be applied to the remaining variables. The *RSL* significantly negatively affects the WRCP in all categories. That means, in reverse, that the WRCP increases for products with low remaining shelf lives. A one-unit decrease in RSL, i.e., one day less remaining shelf life, is associated with an increase in the WRCP ranging from 0.2 pp. in the Delicacies category to 0.5 pp. in all other categories. Further, the *EDVariety* exhibits a significant positive effect across all categories. This is not surprising since multiple (i.e., two or more) EDs on the shelf are the prerequisite for customer picking. However, it also implies that a high number of different EDs on the shelf triggers customers to pick fresher items. A one-unit increase in the ED variety is associated with an increase in the WRCP ranging from 4.7 pp. for Convenience and Milk/Dairy products to 7.4 pp. for the Cheese category. For the item-specific variables, we see that the *RetailPrice* yields a significant impact on the WRCP in the Delicacies and Milk/Dairy category. A one Euro price increase is associated with a 2.3 pp. and a 4.7 pp. increase in the WRCP, respectively. Finally, we find a significant association between *organic* products in the Milk/Dairy category and the WRCP. The control variables considered do not yield a significant effect.

Robustness checks We compute several robustness checks to strengthen our findings. Detailed analysis results are provided in the Appendix.

(i) Product category interaction effects – To avoid any bias due to the different sample sizes of the product category samples, we run the regression model defined in Equation (4.6) with the combined data set and use interaction terms with the treatment variables. In line with our main contribution, we find directionally similar and heterogeneous effects between the product categories (see Table 4.A1 in the Appendix). We also execute the robustness check (ii) and (iii) with interaction terms. Again, standard errors are clustered at the store level.

(ii) Avoiding extreme values for the target variable WRCP – Initially, we considered all observations for our models. As a robustness check, we exclude observations with less than ten waste bookings throughout our data collection period (i.e., we consider only item-store combinations with a minimum of one waste booking per month). This is plausible as observations with low waste bookings have a tendency towards the extreme values of

0 and 1 for the WRCP. Even though this manipulation limits our data set to $44,487$ observations, the effects described in the results section turn out to be robust in the split sample regression (see Table 4.A2 in the Appendix) and in the regression with interaction terms (see Table 4.A3 in the Appendix).

(iii) Boundary condition for delivery matching – The method described in Section 4.4 assumes a range of four days (-2,-1,ED,+1) for delivery matching. This time frame is chosen based on the retailer's guidelines and the interviews with regional management and store employees. As products can be sold until the closing of business on the expiry day, they can be removed on the next morning. As a robustness check, we adjust this time frame in both directions: First, to three days (-2,-1,ED), assuming that all expired products are removed from the shelf until the day of expiration. Second, to five days (-2,-1,ED,+1,+2), assuming that the shelf removal might be delayed by Sundays and public holidays. We attempt the same analysis for customer picking waste identification and run our models again. We achieve directionally the same results for the main effects and confirm the robustness of both manipulations (see Table 4.A4 and 4.A5 for the range (-2,-1,ED) and Table 4.A6 and 4.A7 for the range (-2,-1,ED,+1,+2) in the Appendix). Again, standard errors are clustered at the store level.

(iv) Unobserved variability specific to individual stores or items – Our sample includes data from 1,809 items across 211 stores. Observations from within the same store or related to the same item across different stores tend to be more similar than observations randomly sampled from the entire population. Hierarchical linear modeling (HLM) is applied to account for the nested structure in stores and items (SKUs). The HLM assumes an identity link function for our continuous outcome variable. We follow the stepwise approach suggested by Raudenbush and Bryk (2002) for the entire conditional data set ('All categories'). First, the null model (denoted as Model 0 in Table 4.A8 in the Appendix) without level-wise predictor variables is estimated. The predictor variables are then included step by step (see Models 1-3) until we derive the full model. We compute Models 0

to 3 using the statistic software R-4.3.1 and the lme4 package. The results remain consistent across models, with the final model demonstrating the best fit (see AIC, BIC, and Log Likelihood). Therefore, we can focus on Model 3 for the robustness check. We achieve the same results for the main effects directionally and confirm the robustness of this manipulation.

4.6 Discussion

This paper contributes by developing a novel method to quantify waste caused by customer picking in grocery retail when ED information on batch level is available. In cooperation with our retail partner, we implemented a process adaption and collected so far missing ED data at the warehousing stage. Based on the proprietary data set generated, we were able to quantify the extent of customer picking waste with real-world data and to investigate store and product-related drivers. The latter allows us to derive managerial insights on potential options for retailers to prevent food waste. In this section, we will summarize our empirical findings, analyze their managerial implications, and highlight our contribution to the literature along our two RQs (Sections 4.6.1 and 4.6.2). We conclude in Section 4.6.3 with a discussion of limitations and suggestions for future research.

4.6.1 Customer picking waste quantification

Empirical findings The share of food waste caused by customer picking observed in our sample is substantial in magnitude. Our empirical findings show that, on average, 45% of the food waste in the chilled assortment is caused by customer behavior violating the retailer's intended FEFO withdrawal sequence. For three of the four investigated product categories, the WRCP ranges between 43% and 49%. We observe the lowest WRCP with, on average, 28% for the Convenience category, which comprises mainly products intended for direct consumption.

Managerial implications The extent of the WRCP in our sample is alarming for retailers. The retail industry has long accepted waste as an unavoidable consequence of the high availability of perishable products. Our results indicate that our retail partner can address almost half of its food waste without compromising on availability. Customer picking waste occurs, although the demand was high enough to sell off all items before product expiration. This waste could have been prevented if customers had adhered to the retailer's intended FEFO withdrawal sequence. Hence, it is crucial for retailers to understand potential drivers of customer picking waste and develop mitigation strategies. The process adaption in the warehouse and method for customer picking waste identification can be adopted by other retailers to estimate their WRCP. This transparency can substantiate a profound cost/benefit analysis and guide retailer's strategy for food waste prevention.

Contribution to literature The literature stream related to modeling approaches reviewed in Section 4.2 leverages the withdrawal behavior as an input factor to demand and inventory models to simulate that FEFO customers cause retail food waste. To move from model-based insights to actually quantifying customer picking waste, we take a data-driven approach based on empirical data. Our paper presents the first and so far only empirical study building on retail data to investigate the impact of customer picking on retail food waste. While modeling approaches only simulate the impact of LEFO and FEFO customers (see, e.g., van Donselaar and Broekmeulen, 2012; Tromp et al., 2016; Buismann et al., 2020), we quantify the amount of food waste caused by customer picking and reveal a WRCP of 45% in our research setting. Similar to Broekmeulen and van Donselaar (2019b), our applied method also leverages sales, waste, and inventory data but is designed to quantify customer picking waste and not to estimate the withdrawal behavior.

4.6.2 Customer picking waste driver identification

Empirical findings Building on the results of the customer picking waste quantification, we took an exploratory approach to identify product and store-related drives of the WRCP. All variables considered (WeeklySales, RSL, EDVariety, EDPricing, RetailPrice, and Organic) yield a significant effect on the WRCP. The effect size and significance level differ across product categories, but the effects consistently align in the same direction. The R^2 values, falling within the range of 14.7% to 17.6%, suggest that there is still a notable portion of the variation in the WRCP that the chosen predictors do not explain.

Managerial implications We find both product-related drivers that may guide retailers toward critical products and indications for mitigation strategies in the scope of retail operations. Consistent across all investigated product categories, products with shorter shelf lives are especially prone to picking waste. The remaining shelf life upon arrival at the store depends on the product characteristics and the efficiency of retail operations. Hence, minimizing throughput times from the supplier to the shelf is crucial. Further, after arriving at the store, our results indicate that some products require special attention in shelf operations. As shelf maintenance is costly, retailers should prioritize products with high turnover rates across all categories. Specifically in the Milk/Dairy and Delicacies category, the retail price and the organic label increase WRCP.

Moreover, our results indicate that retailers can mitigate customer picking waste in all categories by limiting the ED variety on the shelf and by applying ED-based pricing for soon-to-expire products. So far, retailers are striving for on-shelf availability without considering the effects of ED accumulation. Our findings suggest that actively managing the amount of different EDs on the shelf can prevent food waste. One way to accomplish this is by reducing the replenishment frequency of stores and shelves. In case retailers can achieve ED visibility on the batch level, as we did in our study, a long-term effort might be to consider insights into the inventory compositions in the replenishment policies and to prevent ED accumulation early on. However, a total cost analysis is required to solve the trade-off between lower replenishment frequencies, higher out-of-stock risks, and aging inventories. A second mitigation strategy for customer picking waste is ED-based pricing. By giving discounts for soon-to-expire products, retailers can stimulate demand for products that would otherwise remain on the shelf and convert into food waste. However, processing costs, lower margins, cannibalization effects, and implications on the brand image have to be considered.

Contribution to literature We contribute to the small body of literature working with retail data collected in the field. Our scope is on perishable products with a maximum of eight weeks (56 days) remaining shelf life upon arrival at the store. We extend the findings of pertinent literature on customer picking by quantifying the implications on food waste. Hansen et al. (2023) and Winkler et al. (2023b) both show that decreasing remaining shelf life increases customer picking. In line with those findings, we show that a decreasing remaining shelf life also materializes in food waste caused by customer picking. Further, Hansen et al. (2023) reveal that discounts mitigate customer picking and Winkler et al. (2023b) identify the ED variety as a driver for customer picking. We highlight that these drivers of customer picking are also in line with the drivers of food waste caused by customer picking. Applying price discounts and limiting the ED variety on the shelf significantly decrease the WRCP. Beyond that, we contribute by revealing that products with high turnover rates (across all categories) and higher-priced and organic products (for selected categories) are especially prone to customer picking waste.

4.6.3 Limitations and future research

Limitations We leveraged a proprietary data set with ED information to quantify the extent of customer picking waste in retail stores. There are some limitations to our approach. First, we are only able to observe the effect of customer picking on retail food waste but cannot observe the number of customers or sales actually violating the FEFO withdrawal sequence. As our logic always requires a waste booking to investigate the effect of customer picking, FEFO violations that do not lead to retail food waste cannot be quantified. Second, our study covers nine months, focusing on a single retailer. The limited period does not allow us to analyze long-term patterns and limits the generalisability of our results for the retail industry. Finally, we were not able to monitor store operations in all stores over the entire data collection period. Even though we conducted field visits and, in addition, regional management and store managers regularly checked adherence to the retailer's policies, we cannot completely exclude the possibility of a temporary disruption in FEFO shelf arrangement.

Future research Our method for customer picking waste identification can be adopted by other researchers to explore issues beyond the scope of our study. This study was conducted in collaboration with a full-range retailer, and stores in our sample are located in Germany. Given that customer behavior can vary depending on the context, future research may consider replicating our study in diverse settings and across various retail formats, such as discounters or hypermarkets, to account for distinct customer segments. Further, future research could investigate different assortments. The impact of customer picking might be especially relevant for fruits & vegetables. However, as those products do not carry ED labels, a different approach is required. Even though we have quantified customer picking waste and identified drivers, further empirical research is required to investigate the impact of potential mitigation strategies on retail food waste. For example, future research could investigate options to impact withdrawal behavior by retailers' store operations, e.g., shelf design or replenishment operations. In this context, future research could explore the connection between customer picking waste at the retail stage and household food waste. By examining the entirety of food waste at both the retail and household levels, it should be investigated whether food waste can genuinely be mitigated through interventions at the retail stage or if it only shifts the burden to the household level.

Appendix

Variables	Est.	SE
(Intercept)	0.292	0.011***
Cheese : WeeklySales	0.109	0.003***
Convenience : WeeklySales	0.108	0.004***
Milk/Dairy : WeeklySales	0.111	0.002***
Delicacies : WeeklySales	0.115	0.002***
Cheese : RSL	-0.004	0.000***
Convenience : RSL	-0.004	0.000***
Milk/Dairy : RSL	-0.004	0.000***
Delicacies : RSL	-0.003	0.000***
Cheese : EDVariety	0.094	0.013***
Convenience : EDVariety	0.062	0.013***
Milk/Dairy :EDVariety	0.047	0.009***
Delicacies: EDVariety	0.050	0.008***
Cheese : EDPricing	-0.202	0.037***
Convenience : EDPricing	-0.424	0.067***
Milk/Dairy : EDPricing	-0.288	0.020***
Delicacies : EDPricing	-0.145	0.021***
Cheese : RetailPrice	0.013	0.004***
Convenience : RetailPrice	0.017	0.005**
Milk/Dairy : RetailPrice	0.048	0.003***
Delicacies : RetailPrice	0.018	0.002***
Cheese : Organic	0.011	0.013
Convenience : Organic	-0.027	0.067
Milk/Dairy : Organic	0.026	0.004***
Delicacies : Organic	0.014	0.006*
SalesArea	0.000	0.000
UrbanLocation	0.002	0.008
R^2	0.174	
$Adj.R^2$	0.174	
Observations	133,911	

Note: *p<0.05; **p<0.01; ***p<0.001
Standard errors (SE) are clustered on a store level.

Table 4.A1: Robustness check (i) – Product category interaction effects

	Cheese		Convenience		Delicacies		Milk/Dairy		All categories	
Variables	**Est.**	**SE**	**Est.**	**SE**	**Est.**	**SE**	**Est.**	**SE**	**Est.**	**SE**
(Intercept)	0.249	0.023***	0.247	0.042***	0.192	0.016***	0.231	0.017***	0.238	0.013***
WeeklySales	0.113	0.005***	0.106	0.007***	0.101	0.003***	0.124	0.003***	0.116	0.002***
RSL	-0.004	0.001***	-0.003	0.001***	-0.004	0.000***	-0.005	0.000***	-0.005	0.000***
EDVariety	0.095	0.018***	-0.013	0.020	0.077	0.012***	0.034	0.012**	0.052	0.009***
EDPricing	-0.110	0.051*	-0.572	0.156***	-0.132	0.024***	-0.280	0.027***	-0.167	0.018***
RetailPrice	-0.005	0.005	0.020	0.016	0.030	0.003***	0.046	0.004***	0.023	0.002***
Organic	0.054	0.024*	0.073	0.160	-0.009	0.009	0.032	0.005***	0.033	0.004***
SalesArea	0.000	0.051	0.001	0.052	0.001	0.047	0.000	0.070	0.000	0.051
UrbanLocation	0.013	0.013	-0.009	0.018	0.014	0.008	0.021	0.012	0.016	0.010
R^2	0.289		0.223		0.232		0.230		0.246	
$Adj.R^2$	0.288		0.218		0.231		0.229		0.246	
Observations	4,101		1,244		13,013		26,129		44,487	

Note: *p<0.05; **p<0.01; ***p<0.001; Standard errors (SE) are clustered on a store level.

Table 4.A2: Robustness check (ii) – Avoiding extreme values - split sample

Variables	**Est.**	**SE**
(Intercept)	0.223	0.014***
Cheese : WeeklySales	0.114	0.005***
Convenience : WeeklySales	0.104	0.007***
Milk/Dairy : WeeklySales	0.124	0.003***
Delicacies : WeeklySales	0.101	0.003***
Cheese : RSL	-0.004	0.001***
Convenience : RSL	-0.002	0.001**
Milk/Dairy : RSL	-0.005	0.000***
Delicacies : RSL	-0.005	0.000***
Cheese : EDVariety	0.100	0.018***
Convenience : EDVariety	-0.011	0.019
Milk/Dairy :EDVariety	0.036	0.011**
Delicacies: EDVariety	0.071	0.012***
Cheese : EDPricing	-0.120	0.051*
Convenience : EDPricing	-0.629	0.116***
Milk/Dairy : EDPricing	-0.286	0.027***
Delicacies : EDPricing	-0.122	0.024***
Cheese : RetailPrice	-0.002	0.005
Convenience : RetailPrice	0.024	0.009**
Milk/Dairy : RetailPrice	0.047	0.004***
Delicacies : RetailPrice	0.027	0.002***
Cheese : Organic	0.056	0.024*
Convenience : Organic	0.062	0.155
Milk/Dairy : Organic	0.032	0.005***
Delicacies : Organic	-0.008	0.009
SalesArea	0.024	0.051
UrbanLocation	0.017	0.010
R^2	0.249	
$Adj.R^2$	0.249	
Observations	44,487	

Note: *p<0.05; **p<0.01; ***p<0.001
Standard errors (SE) are clustered on a store level.

Table 4.A3: Robustness check (ii) – Avoiding extreme values - interaction terms

	Cheese		Convenience		Delicacies		Milk/Dairy		All categories	
Variables	**Est.**	**SE**	**Est.**	**SE**	**Est.**	**SE**	**Est.**	**SE**	**Est.**	**SE**
(Intercept)	0.319	0.021***	0.268	0.022***	0.173	0.012***	0.252	0.015***	0.229	0.012***
WeeklySales	0.095	0.003***	0.087	0.004***	0.097	0.002***	0.093	0.002***	0.095	0.001***
RSL	-0.004	0.000***	-0.003	0.000***	-0.001	0.000***	-0.004	0.000***	-0.003	0.000***
EDVariety	0.057	0.014***	0.027	0.012*	0.059	0.009***	0.047	0.010***	0.055	0.007***
EDPricing	-0.395	0.086***	-0.062	0.069	-0.135	0.031***	-0.204	0.046***	-0.185	0.025***
RetailPrice	0.001	0.003	-0.011	0.006	0.020	0.002***	0.030	0.003***	0.020	0.002***
Organic	0.020	0.013	0.008	0.062	0.010	0.006	0.033	0.004***	0.029	0.003***
SalesArea	0.000	0.001	-0.001	0.001	0.000	0.000	0.000	0.001	0.000	0.000
UrbanLocation	-0.007	0.012	0.001	0.012	0.012	0.008	0.002	0.012	0.003	0.010
R^2	0.145		0.108		0.131		0.117		0.138	
$Adj.R^2$	0.145		0.107		0.130		0.117		0.137	
Observations	13,968		7,926		44,835		67,182		133,911	

Note: *p<0.05; **p<0.01; ***p<0.001; Standard errors (SE) are clustered on a store level.

Table 4.A4: Robustness check (iii) – Boundary condition for delivery matching (-2,-1,ED) - split sample

Variables	**Est.**	**SE**
(Intercept)	0.236	0.012***
Cheese : WeeklySales	0.109	0.000***
Convenience : WeeklySales	0.108	0.008***
Milk/Dairy : WeeklySales	0.111	0.003***
Delicacies : WeeklySales	0.115	0.004***
Cheese : RSL	-0.004	0.002***
Convenience : RSL	-0.004	0.002***
Milk/Dairy : RSL	-0.004	0.000***
Delicacies : RSL	-0.003	0.000***
Cheese : EDVariety	0.094	0.000***
Convenience : EDVariety	0.062	0.000**
Milk/Dairy :EDVariety	0.047	0.012***
Delicacies: EDVariety	0.050	0.012***
Cheese : EDPricing	-0.202	0.009***
Convenience : EDPricing	-0.424	0.008
Milk/Dairy : EDPricing	-0.288	0.037***
Delicacies : EDPricing	-0.145	0.074***
Cheese : RetailPrice	0.013	0.020**
Convenience : RetailPrice	0.017	0.021
Milk/Dairy : RetailPrice	0.048	0.004***
Delicacies : RetailPrice	0.018	0.006***
Cheese : Organic	0.011	0.003
Convenience : Organic	-0.027	0.002
Milk/Dairy : Organic	0.026	0.013***
Delicacies : Organic	0.014	0.066
SalesArea	0.000	0.004
UrbanLocation	0.002	0.006
R^2	0.140	
$Adj.R^2$	0.140	
Observations	133,911	

Note: *p<0.05; **p<0.01; ***p<0.001
Standard errors (SE) are clustered on a store level.

Table 4.A5: Robustness check (iii) – Boundary condition for delivery matching (-2,-1,ED) - interaction terms

Variables	Cheese Est.	Cheese SE	Convenience Est.	Convenience SE	Delicacies Est.	Delicacies SE	Milk/Dairy Est.	Milk/Dairy SE	All categories Est.	All categories SE
(Intercept)	0.415	0.021***	0.462	0.025***	0.309	0.010***	0.350	0.014***	0.349	0.011***
WeeklySales	0.115	0.003***	0.120	0.004***	0.125	0.002***	0.119	0.002***	0.119	0.001***
RSL	-0.005	0.000***	-0.006	0.000***	-0.003	0.000***	-0.005	0.000***	-0.005	0.000***
EDVariety	0.079	0.013***	0.050	0.014***	0.069	0.008***	0.053	0.009***	0.066	0.006***
EDPricing	-0.217	0.038***	-0.320	0.083***	-0.159	0.020***	-0.328	0.020***	-0.240	0.013***
RetailPrice	0.009	0.004*	0.002	0.008	0.025	0.002***	0.051	0.003***	0.031	0.001***
Organic	-0.004	0.013	0.001	0.067	0.011	0.006	0.029	0.004***	0.024	0.003***
SalesArea	-0.001	0.001	-0.001	0.001	0.000	0.000	0.000	0.001	0.000	0.000
UrbanLocation	-0.014	0.011	0.001	0.012	0.008	0.007	-0.002	0.010	0.000	0.008
R^2	0.200		0.179		0.196		0.180		0.200	
Adj.R^2	0.199		0.179		0.196		0.180		0.200	
Observations	13,968		7,926		44,835		67,182		133,911	

Note: *p<0.05; **p<0.01; ***p<0.001; Standard errors (SE) are clustered on a store level.

Table 4.A6: Robustness check (iii) – Boundary condition for delivery matching (-2,-1,ED,+1,+2) - split sample

Variables	Est.	SE
(Intercept)	0.352	0.011***
Cheese : WeeklySales	0.116	0.003***
Convenience : WeeklySales	0.122	0.004***
Milk/Dairy : WeeklySales	0.119	0.002***
Delicacies : WeeklySales	0.125	0.002***
Cheese : RSL	-0.004	0.000***
Convenience : RSL	-0.005	0.000***
Milk/Dairy : RSL	-0.005	0.000***
Delicacies : RSL	-0.003	0.000***
Cheese : EDVariety	0.096	0.012***
Convenience : EDVariety	0.078	0.012***
Milk/Dairy :EDVariety	0.051	0.009***
Delicacies: EDVariety	0.059	0.008***
Cheese : EDPricing	-0.227	0.037***
Convenience : EDPricing	-0.493	0.074***
Milk/Dairy : EDPricing	-0.325	0.020***
Delicacies : EDPricing	-0.159	0.021***
Cheese : RetailPrice	0.015	0.004***
Convenience : RetailPrice	0.025	0.006***
Milk/Dairy : RetailPrice	0.050	0.003***
Delicacies : RetailPrice	0.021	0.002***
Cheese : Organic	-0.005	0.013
Convenience : Organic	-0.039	0.066
Milk/Dairy : Organic	0.028	0.004***
Delicacies : Organic	0.012	0.006*
SalesArea	0.000	0.000
UrbanLocation	0.000	0.008
R^2	0.202	
Adj.R^2	0.202	
Observations	133,911	

Note: *p<0.05; **p<0.01; ***p<0.001
Standard errors (SE) are clustered on a store level.

Table 4.A7: Robustness check (iii) – Boundary condition for delivery matching (-2,-1,ED,+1,+2) - interaction terms

Variables	Model 0	Model 1	Model 2	Model 3
(Intercept)	0.411***	0.352***	0.295***	0.291***
WeeklySales		0.120***	0.124***	0.124***
RSL		-0.004***	-0.004***	-0.004***
EDVariety		0.032***	0.028***	0.028***
EDPricing		-0.112***	-0.170***	-0.170***
RetailPrice			0.030***	0.030***
Organic			0.015*	0.015*
SalesArea				0.000
UrbanLocation				0.004
AIC	107,542.27	96,073.76	95,937.37	95,962.49
BIC	107,581.49	96,152.20	96,035.42	96,080.15
Log Likelihood	-53,767.14	-48,028.88	-47,958.68	-47,969.25
Observations	133,911	133,911	133,911	133,911
Num. groups: SKU	1,809	1,809	1,809	1,809
Num. groups: Store	211	211	211	211
Var: SKU (Intercept)	0.025	0.007	0.007	0.007
Var: Store (Intercept)	0.005	0.003	0.003	0.003
Var: Residual	0.126	0.117	0.117	0.117

$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table 4.A8: Robustness check (iv) – Unobserved variability specific to individual stores or items (Hierarchical linear modeling)

5 Customer Picking for Expiration Dates – Evidence from the Field

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In submission process as of October 25, 2023

Abstract This paper studies undesirable customer picking for expiration dates (EDs) in grocery retail. This opportunistic withdrawal behavior of self-service store customers leads to disorder on shelves, damaged products, and leaves products with shorter EDs on the shelves. It is seen as a major driver for food waste at the retail stage. We collaborated with a leading European grocery retailer to collect so far missing ED data. As barcodes do not contain ED information, data was manually collected by periodic stocktaking over five weeks in six stores in parallel. Based on this novel field data, we are able to quantify the extent of undesirable customer picking and investigate store operations to mitigate it. We find that, on average, at least every fourth (lower bound= 26%) and at most every third (upper bound= 35%) customer withdrawal undermines the retailer's intended first-expire-first-out sequence. Further, we apply a hierarchical generalized linear modeling to investigate retailers' options in shelf design and replenishment that might impact undesirable customer picking for EDs. We reveal proactive mitigation options by identifying the impact of the vertical shelf level, the product presentation, the grabbing space, the shelf space assignment, the remaining shelf life, and the ED variety on undesirable customer picking. Moreover, we show that the commonly applied assumptions in modeling approaches are misleading to estimate customer withdrawal behavior. Our study builds the empirical foundation to integrate customer withdrawing behavior depending on the remaining shelf life of the foremost product, the ED variety, and customers' effort in picking a fresher product in future modeling approaches.

5.1 Introduction

Fresh products play a pivotal role in grocery retailing. Customers' choice of stores and products is heavily influenced by the freshness level of the products (Tsiros and Heilman, 2005; Broekmeulen and van Donselaar, 2016) and their availability (see, e.g., Honhon et al., 2010). Ensuring both at the same time is crucial for retailers to maintain store traffic, customer loyalty, and revenue generation. However, perishable products are more complex to manage (Akkaş et al., 2018; Winkler et al., 2023a) as they can only be sold before expiration. Excess inventory or improper handling can result in waste emergence, monetary losses, and, above all, social and environmental concerns related to food waste Akkaş and Gaur (2022). Shrink costs are, on average, 2 to 3% of a typical grocer's total sales (McKinsey, 2020). The freshness requirement necessitates the frequent replenishment of shelves. It is common retailer practice to push new deliveries into the store before the old inventory is completely sold (see, e.g., Akkaş and Honhon, 2023). The continuous replenishment ensures freshness and availability but also leads to multiple expiration dates (EDs) of the same product on the shelf. Retailers intend the customer always to pick the first item displayed on the shelf (see products with ED (1) in Figure 5.1). They consequently organize the shelves such that older products are in the front and freshly replenished products are refilled from the back. The so-called inventory rotation ensures that products are sold in the order of their impending expiration, i.e., first-to-expire products are sold first (Reiner et al., 2013).

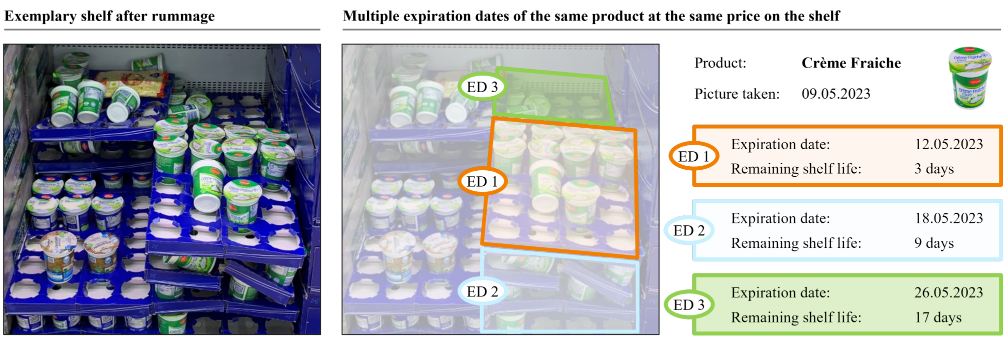

Figure 5.1: Example of undesirable customer picking

Despite the retailers' inventory rotation, customers are well aware of the availability of different EDs for the same products that are sold for the same price. The relevance of EDs for customers is shown in a survey among 26,601 respondents across 28 European countries, revealing that 81% 'always' or 'often' check date labels when shopping for groceries (TNS political & social, 2015). Customers may seek fresher products or increase their possible consumption time range. They may rummage within the shelves to pick items further behind or below (see empty slots in the cardboard for products with ED (2) and ED (3) in Figure 5.1). Self-service store customers may hence undermine the retailer's intention and reach for potentially fresher product units at the back of shelves.

We denote the customers' withdrawals that violate the first-expire-first-out (FEFO) principle by selecting products with more distant EDs as *undesirable customer picking*. This is problematic for retailers as it can cause disorder on shelves, damage products, and leaves products with shorter EDs on the shelf (see example above, and, e.g., Akkaş, 2019; Clarkson et al., 2023). It potentially leads to food waste when customers systematically pick for extended EDs, leaving near-to-expire products on the shelves (see, e.g., Akkaş and Gaur, 2022; Winkler et al., 2023a). Retailers see customer picking as a major driver for food waste and inventory issues: *"Clearly the percentage of waste is considerably higher when all consumers buy only the freshest items on the shelf"* (Broekmeulen and van Donselaar, 2016). The unintended customer interventions on fresh products cause not only disorganized shelves but also perpetual inaccuracies that degrade retailers' trust in inventory data and "ultimately lead to lost profits via excessive shrink, out-of-stocks, less fresh food, wasted labor, and more" (Afresh, 2023a,b). Schaefer et al. (2024) show that customer picking is responsible for almost half of the food waste at stores. The awareness of this problem and its consequences in daily business also bothers our retail partner and facilitates the need to quantify undesirable customer picking. Customer picking has been seen as the major driver for food waste at this retailer. These all together raise the questions of to what extent customers pick for a more distant ED and what are the drivers for this behavior?

While acknowledging the importance of withdrawal behavior into store operations and its planning (see, e.g., Akkaş and Gaur, 2022; Riesenegger et al., 2023), modeling and analytical research lacks empirical foundation in this regard. The literature on consumer behavior concerning EDs, on the other side, is limited to theoretical insight lacking actual conditions in a store (see, e.g., Tsiros and Heilman, 2005; Hansen et al., 2023). They explore customer motivation (e.g., product quality, nutrition aspects) with surveys but lack insights into mitigation options to limit the undesirable picking. Akkaş and Gaur (2022) call for research to prevent customers from picking the freshest item from the shelf to prevent food waste. Limiting ED visibility has been so far the only identified proactive mitigation option in literature (see, e.g., Tsiros and Heilman, 2005). However, this is out of the retailer's control as the ED label is part of the manufacturer's product design. Options to impact withdrawal behavior by retail store operations (e.g., less grabbing space, availability of different EDs) have not been investigated so far. The actual share of customers picking fresher products is unknown, in particular as the scanner data do not include any ED information (see Hansen et al., 2023). We follow an exploratory approach to address this research gap. Our study aims to quantify the extent of customer picking for fresher products and identify options for the retailer for proactive mitigation within the scope of retail operations. To do so, we collected inventory, shelf, and sales data within the scope of a cooperation with a leading European grocery retailer. Within 700 hours of manual data collection, we obtained more than 28,000 observations for 42 products of 14 product groups across six stores during five weeks.

The remainder is structured as follows. Section 5.2 analyzes related literature. Section 5.3 defines the retail context and identifies the potential options of a retailer within store operations to mitigate picking. The data collection process is detailed in Section 5.4, whereas Section 5.5 details the econometric analysis. Section 5.6 discusses the empirical findings on undesirable customer picking, derives theoretical and managerial implications, and elaborates on limitations and future research.

5.2 Related literature on customer picking in retail stores

This section reviews related literature that can be agglomerated into two different streams. The first stream investigates customer attention of EDs, whereas the second stream incorporates customer withdrawal into shelf space, pricing, and inventory optimization.

(1) Consumer studies on expiration date attention A small body of consumer studies analyzes how many and why customers search for the ED. These studies seek to illuminate the role of the ED in information search. In a seminal paper, Tsiros and Heilman (2005) investigate the customers' attention to EDs through a survey. They show that customers attempt to reduce the risk of buying close-to-expire products by searching for product attributes before purchasing. The study reveals that the share of ED search varies by food category, ranging from 29% for precut carrots to 93% for milk. The differences between categories are explained by the perceived quality risk of a category (e.g., salmonella in eggs). The greater the quality risks associated with a product, the more frequently consumers check EDs. Furthermore, consumers with greater category experience search ED more frequently. Finally, the authors found that the customers' willingness-to-pay increases with longer remaining shelf life. Harcar and Karakaya (2005) conducted a cross-country survey and show that ED attention differs between countries. This is attributed to differing risk aversions embedded in the cultures and the customers themselves. For example, health-conscious consumers may pay more attention to EDs. The authors highlight that the ED visibility at the product and the related search effort have a negative impact on consumers' motivation to check EDs. In a more recent study, Shah and Hall-Phillips (2018) also show that ED search effort is influenced by perceived quality risk and the customer's motivation to check EDs. They are the first to show that time-pressured grocery customers reduce the ED search effort. Choi et al. (2022) explore consumers' aversion to near-expiry food at the purchase stage. Like the studies before, they confirm the negative impact of short remaining shelf life and product quality risk (here in the context of healthy nutrition) on purchase intention. Hansen et al. (2023) present the first field experiment in a related area. They explore consumer response to ED-dependent pricing, where the retailer reduces the price according to the remaining shelf life of one product group (fresh meat) in one store. They track customer choices at the ED level by collecting transaction line, inventory, and shelf price panel data where expanded barcodes and electronic shelf labels have been implemented in a pilot study. As in almost half of all purchases, consumers choose an older item when a fresher one is available; the authors claim it as consumer inattention to EDs. They further show that the FEFO arrangement of products within a shelf increases the share choice of the oldest item by 24 percentage points compared to a disorganized shelf without inventory rotation. Further, consumers pay less attention to the ED when the top-facing item has a longer remaining shelf life. The informed choices of products decrease with choice frictions and search costs.

To summarize, insights from the consumer studies indicate that customers pay attention to EDs and that preferences depend, among others, on the visibility of the ED at the product (e.g., Harcar and Karakaya, 2005) and related search effort (e.g., Hansen et al., 2023), category experience (Tsiros and Heilman, 2005), the customers' motivation to check EDs (e.g., to reduce the perceived quality risk of a product (Tsiros and Heilman, 2005; Choi et al., 2022) or because of health/nutrition considerations (Harcar and Karakaya, 2005)), remaining shelf life of products (Hansen et al., 2023), and the available time for grocery shopping (Shah and Hall-Phillips, 2018). Although highlighting the importance of customers' concerns about ED attention, the studies do not yet connect it with undesirable customer picking and retail operations. They do not develop proactive prevention options that a retailer can take to mitigate it. Despite Hansen et al. (2023) identifying the willingness-to-pay for close-to-expire products, the ED-dependent pricing constitutes only a reactive measurement to salvage overstocks. Although they show the negative effect of organized shelves (i.e., FEFO arrangement) on picking, not rotating products is rather a hypothetical scenario as adherence to FEFO arrangement is standard in any store. Furthermore, findings of Hansen et al. (2023) are limited to the particular shelf type of a refrigerated cabinet where products are stapled, and customers observe only products from above. The potential impact of further proactive mitigation options within store operations like shelf design (e.g., vertical shelf level, cardboard presentation) and replenishment policies (e.g., available EDs) is impossible or was not considered to be investigated in this particular shelf type. A further limitation of most studies (except Hansen et al. (2023)) is the reliance on surveys. They do not obtain direct insights from the field, and their implications are studied in purely theoretical models (Hansen et al., 2023). However, there are many other determinants for the actual purchasing behavior and ED attention as the shopping is impacted by an environment which is “rushed, noisy and full of external cues” (Hansen et al., 2023, p. 5).

(2) Modeling approaches incorporating withdrawal behavior A growing body of analytical and modeling literature deals with customer withdrawal behavior when determining prices, shelf space, and inventory. In a recent review, Riesenegger et al. (2023) identify related problems and show that the withdrawal behavior is input to demand and inventory models. FEFO withdrawal has been commonly used in the literature to obtain tractable models (see, e.g., Karaesmen et al., 2011; Ketzenberg et al., 2015; Chao et al., 2015; Clarkson et al., 2023). However, this is a strong simplification as the undesirable customer picking by a last-expire-first-out (LEFO) withdrawal is not considered in these models. More advanced approaches differentiate between LEFO and FEFO withdrawals. For example, Akkaş (2019) takes this into account when allocating shelf space, while Buisman et al. (2019) study a dynamic pricing problem and consider a split between LEFO and FEFO customers. In inventory management-related issues, the withdrawal options are already an established input factor in the literature due to the imminent impact on inventory policies (Riesenegger et al., 2023). For example, Ketzenberg et al. (2018), Broekmeulen and van Donselaar (2019a), Zhang et al. (2020), and Clarkson et al. (2023) assume different LEFO/FEFO shares to analyze replenishment policies and show their impact on optimal inventories. However, despite the importance and application of the LEFO/FEFO shares, all modeling and analytical approaches rely only on simulated LEFO/FEFO shares without empirical justification. Potential interrelationships between customer withdrawal and inventory composition or shelf layout are not yet considered. This constitutes a significant research gap as LEFO/FEFO shares may vary.

5.3 Retail setting and its impact on customer picking

The analytical and modeling literature shows the impact of customer withdrawal on inventory development, whereas the consumer studies investigate the ED attention related to the consumer (e.g., nutrition issues), product attributes (e.g., quality risk), and manufacturer-controlled options (e.g., visibility of ED label). The only related reactive option is ED-dependent discounting. Prevention options in the hands of a retailer are not yet explored. Therefore, we will first elaborate on retailers' opportunities within their control and derive potential options that might impact undesirable customer picking. We identify seven options based on several field visits, discussions with experts from the cooperating retailer, and pertinent literature in the retail context. The retailers' options in store operations can be clustered in the two areas: *shelf options* and *replenishment options*.

Potential shelf options to influence customer picking Shelf plans are an essential element of store operations. The planograms are updated regularly on an annual level (Düsterhöft and Hübner, 2023). Possible options for shelf designs comprise the (i) vertical shelf level, (ii) product presentation, (iii) grabbing space, and (iv) shelf space assignment. Figure

5.2 exemplifies a grocery store shelf and the related options that impact store operations and customer behavior.

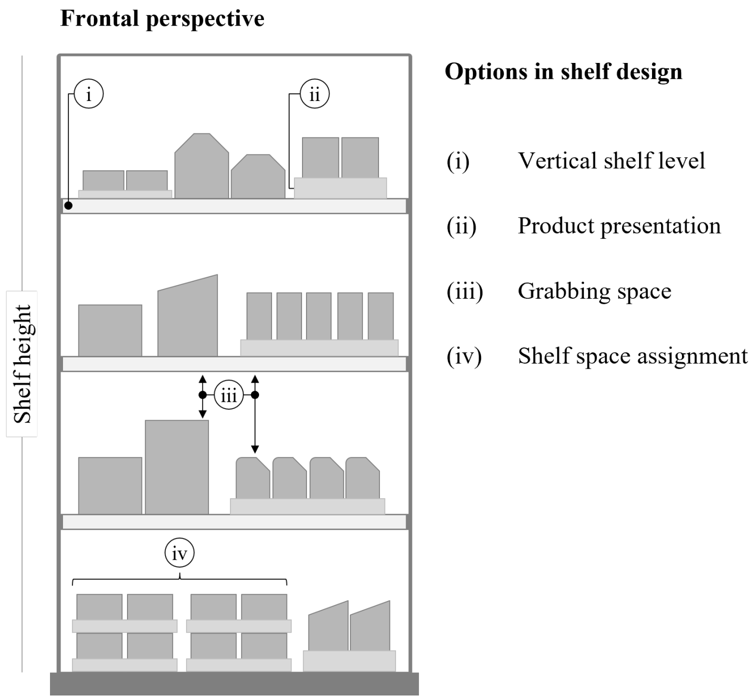

Figure 5.2: Potential options in shelf design to influence customer picking

(i) Vertical shelf level – Products are stored on multiple vertical levels on the shelf (see, e.g., Düsterhöft et al., 2020; Hübner et al., 2021). For example, there are four vertical levels (“ankle”, “waist”,“eye” and “top” level) in Figure 5.2. The probability of a product being seen and purchased changes with the vertical position of an item on the shelf. For example, Drèze et al. (1994) and Chandon et al. (2009) found that products stored in a zone ranging approximately from eye to knee level have the highest chance of being perceived by customers. Beyond that, the vertical shelf level influences the ease of withdrawal for customers. While items from eye to knee level are relatively easy to withdraw, customers might need to bend over or stretch to remove an item from the bottom or top level. In this regard, the levels might impact the undesirable customer picking by the “ease of withdrawal”, i.e., if there is an increased effort to reach a back-row item from the shelf.

(ii) Product presentation – Retailers have two options for presenting the products on the shelves. The first option is using entire case packs where products are stored in the cardboard (see, e.g., the product marked with tracker (ii) in Figure 5.2). A case pack refers to how products are packaged and delivered from the manufacturer. In a case pack, multiple selling units of one product are bundled and shipped in a single cardboard. Case packs are less costly to replenish since multiple units can be stocked at once (see, e.g., Hellström and Saghir, 2007; Wensing et al., 2018). The units in the case pack have an identical ED, as the case pack compromises products from the same production batch. The second option is a single unit presentation (without the case pack; see, e.g., the two products stored to the left of tracker (ii) in Figure 5.2). In this case, the items must be unpacked and stored as single units on the shelf. Single unit refill refers accordingly to the process of restocking products on shelves with unpacked selling units. Breaking up the case packs allows for higher product variety within a store (see, e.g., Ketzenberg et al., 2002; Broekmeulen et al., 2017) and also results from the misalignment of case pack size (determined by the manufacturer) with shelf space and reorder points (determined by retailer) (Eroglu et al., 2013). With a single-unit refill, retailers have more control over their stock quantities based on customer demand and available shelf space. Retailers may use both presentation options to meet the needs of different products on their shelves. The impact of product presentation on customer picking may be ambiguous. On the one side, case packs make it easier for customers to identify and compare different EDs between available cardboards. On the other side, retrieving the units from the different boxes may be more challenging compared to a single unit presentation.

(iii) Grabbing space – The grabbing space of an item on the shelf to the next higher shelf level and to the surrounding items is related to the density of product arrangements and shelf levels (Bianchi-Aguiar et al., 2021; Hübner et al., 2021). It, therefore, defines the room for customers to reach back in the shelf to pick a second or third-row item. Tracker (iii) at Figure 5.2 illustrates the space between the item and the shelf board as well as the space to the surrounding items. Shelf heights are determined so that the

highest item in a row or multiple case packs of a product fit onto the shelf. This leads to different gabbing spaces for individual products depending on the shelf plan. Less grabbing space, and as such, a higher shelf density may reduce customer picking as it increases the effort for customers to pick a back-row item. We distinguish three levels of density (in increasing order): "loose options", where customers can easily reach to the back and withdraw all back row items without rearranging the shelf; "dense options", where customers can reach to the back with minor effort and withdraw some back row items without rearranging the shelf; "very dense options", where customers must rearrange the entire shelf level (i.e., remove first-row items) to withdraw items from the back rows.

(iv) Shelf space assignment – The shelf space assigned to a product is expressed by the number of facings. A facing denotes the foremost unit of an item in the front row of the shelf. For example, in Figure 5.2, four product facings are visualized (see tracker (iv)). The number of facings of a product impacts visibility and sales. If more facings are allocated to a product, it is more likely to be seen by customers in a store and is purchased more frequently (see, e.g., Eisend, 2014). The retailer can also stack products by putting one above another. The total number of facings is then the number of vertical facings times the number of horizontal facings. The stacking of products can usually only be done with case packs and cubic, single-refiled products with stable packaging. Having multiple facings (vertically and horizontally) increases product visibility, signaling to customers that there are possibly different EDs to consider before making a purchase. In contrast, stacking potentially complicates undesirable withdrawal behavior.

Potential replenishment options to influence customer picking The second set of options is determined by the interplay between the retailer's inventory policy (including order-up-to levels), actual customer demand, and the frequency of product replenishment. The options are related to the (v) available inventory, (vi) remaining shelf life, and (vii) ED variety.

(v) Available inventory – It is common retail policy to replenish stocks periodically in fixed time intervals and with a constant order-up-to level (see, e.g., Buismann et al., 2020). This stationary base-stock policy, also labeled as "fill the hole" (see Akkaş, 2019), replenishes the difference between a constant order-up-to level and the current inventory level. The current inventory level results from the order-up-to level minus the sold and expired units. The available inventory has a considerable impact on customers' purchasing behavior (see, e.g., Boada-Collado and Martínez-de Albéniz, 2020; Martínez-de Albéniz and Kunnumkal, 2022). In our context, the inventory level might impact the customers' perception of the expected availability of different EDs. A high inventory level may lead to more customer picking.

(vi) Remaining shelf life – Remaining shelf life refers to the amount of time a product has left before it reaches its ED. The remaining shelf life depends on the arrival date of the product at the store, the overall inventory level, replenishment frequency, and customer demand. The remaining shelf life is a significant piece of information for the customers about the perceived quality of a product (see, e.g., Tsiros and Heilman, 2005). The remaining shelf life decreases over time and reduces the attractiveness of a product (Shah and Hall-Phillips, 2018; Hansen et al., 2023). Tsiros and Heilman (2005) show that the customer's willingness-to-pay decreases linearly, and for some product categories, even exponentially throughout the shelf life. Also, Caro et al. (2014) show that a product's attractiveness reduces over time. More frequent replenishment (e.g., for products with high demand and comparably low order-up-to levels) and the resulting higher inventory turn usually result in products with a higher remaining shelf life. As retailers refill the shelves in a FEFO logic, customers face the first-to-expire item as the foremost unit in the front row of the shelf (denoted as the foremost item in the following). It can be expected that the customer picking increases with a decreasing remaining shelf life of the foremost item (i.e., minimum remaining shelf life).

(vii) Expiration date variety – The frequent replenishment required by stores (e.g., by push-deliveries from the distribution centers) leads to different EDs available on the shelves. The ED variety describes this effect and quantifies the number of available EDs for products. As aforementioned, retailers refill the shelves in a FEFO logic, yet customers are usually aware that multiple EDs are stocked for certain products. The presence of multiple EDs is a prerequisite for customer picking, but may also promote it as it potentially increases customer awareness of EDs and amplifies their possible choices.

After clarifying the retailers' options to impact customer picking, we will move in the following section to the data collection in the field.

5.4 Empirical setting and data

This section details the manual data collection at the retailer in Section 5.4.1 and the subsequent data preparation in Section 5.4.2.

5.4.1 Data collection

Field setting and data Our study is based on primary data from a leading European grocery retailer. Only field data enables us to quantify undesirable customer picking and analyze the effects of different options in store operations (see Section 5.3). Our industry partner is a multi-billion Euro retailer headquartered in Germany that operates >3,500 stores in Europe. The assortment consists of more than 50,000 SKUs (stock keeping units) across several categories, such as ambient, fruits & vegetables, and chilled and frozen products. The stores are supplied by dedicated regional warehouses. Store orders are placed by the retailer's automated forecasting and replenishment system. Daily orders for each SKU are automatically calculated based on current inventory levels, shelf capacities, and demand forecasts. Store managers are technically allowed to modify orders, but interventions are an exception.

We conducted field visits to stores and corporate headquarters to better understand the retailers' existing operations. During these field visits, we observed replenishment practices, interviewed store employees, and met with senior analytics, sales, and supply chain management executives. The study scope and process for data collection were aligned with and approved by the retailer's senior management. The management team considers undesirable customer picking as the major driver for food waste. The qualitative insights were enriched with archival data, including store information (e.g., store type, customer frequency, shelf types, planograms), product level data (e.g., pack sizes, brand), and store-product data (e.g., sales per store).

We focus on products with a fixed shelf life where the EDs are indicated by "best before" (e.g., "best before August-01") or "use by", etc. Such labels are required by law (e.g., within the European Union) or voluntary (e.g., in the US). The labels display the exact date on the packages until the product should be consumed, as determined by the manufacturer. Within the broad spectrum of perishable products, we concentrate on the chilled assortment for two reasons. First, chilled products are standardized and carry ED labels. This is important as the freshness level is less prone to a subjective quality assessment than categories that do not carry ED labels (e.g., fruits & vegetables). Second, chilled products mostly have a short (e.g., 3–6 weeks) to very short (e.g., 1–2 weeks) shelf life upon delivery to stores. The risk of spoilage and with that, the potential effect of undesirable customer picking is higher for chilled products. Other assortment categories, such as ambient (e.g., canned food, rice, or pasta), show a longer shelf life (e.g., longer than 12 months) and are less susceptible to the impacts of customer picking. The retailer distinguishes between six chilled product categories (cheese, convenience, dairy, delicacies, meat, and milk) that are organized into 74 product groups. The retailer's stores show an average of approx. $1,500$ different SKUs in the chilled assortment. The daily shelf replenishment is executed by store employees and ensures that the products are rotated to follow the aspired FEFO arrangement. Usually, one employee is responsible for the chilled assortment in each store. They are responsible for maintaining shelf space and positions as defined in the planogram (e.g., they reorganize the shelf daily after customer rummage). Further, the employee checks EDs and removes expired products from the shelves. In addition to that, store and regional managers monitor compliance with shelf standards, refill practices, and planograms (e.g., on-shelf-availability, sales, and loss) and regularly visit the outlets for quality assurance and employee training.

In general, grocery retailers track their inventories with barcodes. Products are scanned when entering the store and at the cash desk. Yet, as the currently applied barcodes do not include ED information, the retailers lack information on the inventory composition concerning EDs. Consequently, scanner data do not contain any ED information (see also Hansen et al., 2023). These circumstances facilitate the need for manual data collection (i.e., manual checks of the on-shelf inventory) to overcome the missing ED information.

Product and store selection Our manual data collection required to select products and stores to manage the time effort. We conducted the selection process jointly with experts from the retailer (category and store managers). As a data basis, we leveraged sales data from the previous year and product/store master data.

(a) Product selection: It was the retailer's priority that the data collection disrupted the customer shopping as little as possible. This resulted in a single data collector per store at any time. We identified in a pretest that collecting one data point for one product takes an average of 1.5 minutes. As we apply hourly observations, we derived the capacity for approx. 40 products to be included in our sample. Aiming for both a relevant (regarding sales volumes) and heterogeneous sample covering

the assortment's width, we included all six chilled product categories and determined the number of product groups per category by the corresponding revenue share. The product groups selected have the highest turnover in their respective category and constitute the core assortment. We defined 14 groups and three products per group to collect data for 42 products (our capacity limit). The product selection within a group was based again on high sales volumes to ensure relevance (as the retailer's main criteria) and sufficient customer withdrawals during the observation periods. We only included products that were not on promotion before and during the data collection and ensured that all products within one group were substitutes with the same pack size. To control for potential brand and price effects, we included at least one branded and one private-label product in each group. Our ultimate goal is to assess the impact of different practices with regard to shelf plans and replenishment procedures. To investigate the retailers' options in store operations identified in Section 5.3, we made sure that products from different shelf levels (high; mid; low), presentations options (case pack; single unit), grabbing space (loose; dense; very dense) and space assignments (number of facings) are included in our sample within and across the stores. Furthermore, we ensured that the products have various general remaining shelf lives (ultra-fresh; fresh), inventory levels (high; mid; low), and replenishment frequency (very often; often) to have a broader perspective on replenishment policies. Our study focuses on fast-moving products, but we found in pretests that store operations are identical for slow-moving products. Table 5.1 summarizes the central characteristics of the products selected.

Categories	**Dairy**	**Cheese**	**Milk**	**Meat**	**Delicacies**	**Convenience**
Number of SKUs	12	9	6	6	6	3
Number of branded SKUs	6	5	4	4	4	1
Avg. weekly demand[1]	75	76	55	30	32	34
Avg. number of deliveries[2]	1.6	2.1	2.1	1.5	1.6	1.5
Avg. remaining shelf life[3]	27	43	17	21	21	33

[1] Average weekly demand per store and per product selected in category
[2] Average number of weekly deliveries from warehouse, per store and per product selected in category
[3] Average remaining shelf life of products selected in category when products enter the store, in days

Table 5.1: Key characteristics of products for the manual data collection (overview)

(b) Store selection: For the store selection, it was essential to have identical assortments and merchandising processes across the stores. We, therefore, selected one region in Germany to ensure internal homogeneity of stores as the assortments and logistics processes differ across the regions of the retailer. The retailer operates 209 stores in the selected region of Southeast Germany. Among the 209 stores, we applied the following criteria for the selection process. First, we included only stores that have been in operation for at least one year and in which the 42 selected products were constantly listed during that time. Second, selected stores did not apply price discounts for overstocks in the past twelve months to avoid leftover inventory (i.e., discounting of close-to-expire products) as this may impact customers' ED attention (see Hansen et al., 2023). Finally, the number of stores may not exceed six stores, and the stores have to lie in a certain proximity to each other to ensure a feasible data collection process for the team of researchers. Following this process and a continuous alignment with the retailer, we narrowed down the store candidates to a cluster of 34 stores in one geographical region. For the cluster identified, we applied a detailed analysis of the shelf layout presented in Section 5.3 for all selected products to ensure a sufficiently high heterogeneity. Although we could not randomly choose from the entire population, we got access to stores that exhibit diverse characteristics with respect to total store sales, urban and regional areas, large and small stores, and larger and smaller chilled assortments. Despite the number of stores being limited by our capacity for manual data collection, it ensures a sufficiently large sample. The number of stores selected is comparable to other empirical studies in grocery retailing (see, e.g., DeHoratius et al., 2023). Table 5.2 summarizes the central characteristics of the stores selected.

Store	**S01**	**S02**	**S03**	**S04**	**S05**	**S06**
City size[1]	large	medium	small	large	large	small
Location	central	central	residential	residential	industrial	industrial
Number of SKUs[2]	1,365	1,391	1,560	1,525	1,773	952
Sales area[3][in m^2]	887	1,351	1,444	2,050	1,695	1,690

[1] Number of residents: small < 50.000, medium ≥ 50.000, large > 150.000
[2] Number of SKUs in the chilled assortment counted
[3] Sales area of total store

Table 5.2: Key characteristics of stores for manual data collection (overview)

Manual data collection process We designed and executed a series of physical data collections for the selected products and stores. Our research team for data collection consisted of two research associates and a group of students (12 undergraduate, one graduate), who carried out the data collection under our direction. The graduate student and the two research associates supervised the groups and monitored the data collection.

We manually collected data by periodic stocktaking (i.e., counting stock for each product and each available ED) over five weeks between November and December 2021 in all six stores in parallel (excluding the pre-Christmas weeks). This period is a representative sales period at the retailer and does not include major disruptions like peak/low demand weeks or public holidays. Customer picking may only be identified in the event that items of a product are sold between two observations. As a prerequisite from the retailer and to ensure a sufficient number of shelf withdrawals (unit of observation), we focused on the two peak-demand days, namely Fridays and Saturdays. Approximately 50% of the retailers' revenue is generated on these days. Collecting the data on the peak days ensured that we had more sales (and shelf withdrawals) during our data collection (see also above on the criteria for product selection). ED and inventory information were documented hourly, that means at time t and again at time $t + 1$, for each of the 42 products in each of the six stores. To cover the complete opening hours (from 8am to 8pm), we allocated two daily shifts to each store, resulting in more than 700 hours of manual data collection. The shifts overlapped from 2pm to 3pm to ensure a smooth handover from one data collector to the other. Data for the initial inventory for a day at 8am was always separately collected.

Data were first collected with templates and digitized in data sheets (see Appendix, Figure 5.A1). Each observation represents a snapshot of the inventory and corresponding EDs of the 42 products. Each sheet had an integrated data validation (i.e., plausibility checks for ED and quantity entries, including pop-ups highlighting potential abnormalities, e.g., ED in the past). Quality control was done by two research associates right after the data collection. Customer purchases were not interrupted by and during the data collection process. In case a customer or employee occupied a shelf, the affected product was postponed, and data collection continued as soon as the shelf was accessible again. We did not manipulate the supply or demand of the selected products. Orders were placed by the retailer's automated forecasting and replenishment system, and no additional sales incentive was created in the stores (e.g., no product was on promotion, no ED-based discounting). We reorganized the shelves in a FEFO logic once an hour to reflect the retailer's intended FEFO policy and ensured that customers encountered an organized shelf. The hourly inventory and ED data are used to determine the withdrawal behavior. The constitution of the replenishment-related options (v)-(vii) (see Section 5.3) may change from observation to observation. These are time-variant. Additionally, we collected visual material of the general shelf layout once a day. This helped us to control the options related to shelf design for each product-store combination (see (i)-(iv) in Section 5.3). The shelf plan-related options are time-invariant within the scope of this study. The daily snapshot also served as reassurance that the shelf situation remained unmodified throughout the data collection. By ensuring an unmodified shelf situation during the data collection for each product-store combination, we were able to derive in total 252 (42 products $\times$ 6 stores) distinct shelf situations.

5.4.2 Data preparation

Conditional data set The manual data collection results in a total of $28,039$ observations and comprises $26,289$ withdrawn units from the shelf. Considering the full data set, we find that in 50.0% of our observations, only one distinct ED was available on the shelf, and the average out-of-stock share was 4.8%. In total, that means that in 54.8% of our observations, customers could not choose between different EDs. For the instances where customers did have a picking opportunity (45.2%), they could choose between two (37.8%), three (6.4%), or even four or more (0.9%) EDs on the shelf.

We restrict our data set to observations where a picking opportunity was given, excluding out-of-stocks and observations with only one distinct ED on the shelf $(15,378)$. Further, we also exclude records with no withdrawal between two consecutive observations $(7,479)$. As we collected primary data without interrupting store processes, replenishment processes affected some records. If the inventory for a product increases from a distinct point in time, we exclude those observations (318). Further, we exclude records with obvious data errors (e.g., data gaps or product mix-ups) caused by the manual collection process (456). We thus obtain a final data set, denoted as *conditional data set*, that builds the foundation of our analysis. It consists of $n = 4,408$ observations accounting for $m = 11,587$ shelf withdrawals.

Definition of undesirable customer picking for expiration dates

FEFO withdrawal occurs when one of the foremost units with the minimum ED is picked by the customer. In contrast, every shelf withdrawal that is not from the stock of the first-to-expire units constitutes *Undesirable Customer Picking for Expiration Dates* (UCPED). In this case, a unit is withdrawn that does not have the minimum available ED. For the definition of UCPED, we use the set of items I, with $i, i \in I$, and the set of stores $S, s \in S$. The withdrawals are denoted by $w, w \in W$, where W is defined as $W = \{1, \ldots, m\}$. We consider every single shelf withdrawal w identified (i.e., possibly multiple withdrawals between two hourly observations). The classification of each withdrawal w of a product i in store s is then indicated by the binary parameter $u_{w,s,i}$ (see Equation (5.1)).

$$\mathrm{u}_{w,s,i} = \begin{cases} 1, & if \text{ withdrawn ED} > \text{minimum ED} \\ 0, & otherwise \end{cases} \qquad \forall w \in W, s \in S, i \in I. \tag{5.1}$$

Our periodical stocktaking approach does not account for the withdrawal sequence itself as each observation represents an hourly snapshot. The data collection process applied inherently has some ambiguity in the withdrawal sequence when multiple units with different EDs are taken from the shelf. We address this issue by considering different scenarios and account for all withdrawals (incl. the FEFO withdrawals). Figure 5.3 visualizes examples of scenarios in which the classification of withdrawals is not distinct between two consecutive observations. The first stocktaking at 10am shows five units (#1–#5) with three different available EDs on the shelf. The subsequent stocktaking at 11am only shows two remaining units. In this case, different withdrawal sequences are possible. Looking at Scenario 1, (#2) is withdrawn after (#1), and (#2) constitutes a FEFO withdrawal. This contrasts with Scenario 2, where (#2) is removed before (#1), and therefore represents a UCPED. Depending on the withdrawal sequence, (#2) can be either a 'FEFO' or 'UCPED' withdrawal. In this case we classify the withdrawal in our data as 'ambiguous'.

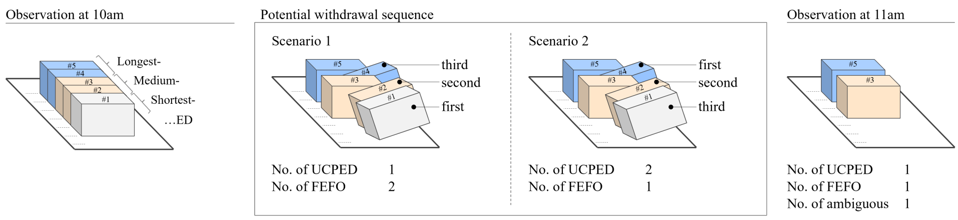

Figure 5.3: Classification of UCPED and FEFO withdrawals (example)

Following this logic, we can distinctly classify 91% of the withdrawals in our data as 'FEFO' or 'UCPED'. Only 9% were classified as 'ambiguous'. Based on the classification, we are able to derive a *lower bound (LB)*, an *approximate (approx)*, and an *upper bound (UB)* for the UCPED share. We assume that all 'ambiguous' withdrawals are 'FEFO' to calculate the LB and assume that all 'ambiguous' withdrawals are 'UCPED' to calculate the UB. The approximate case is calculated by excluding all 'ambiguous' withdrawals and only considering 'FEFO' and 'UCPED' withdrawals. We denote the total number of withdrawals m (see above) and the total number of ambiguously classified withdrawals m^{amb}. We differentiate the respective UCPED shares using LB, approx and UB, and calculate them as follows:

$$\begin{aligned}
\mathrm{UCPED}^{\mathrm{LB}} &= \frac{\sum_{w,s,i} \mathrm{u}_{w,s,i}}{m};\\
\mathrm{UCPED}^{\mathrm{approx}} &= \frac{\sum_{w,s,i} \mathrm{u}_{w,s,i}}{m - m^{\mathrm{amb}}};\\
\mathrm{UCPED}^{\mathrm{UB}} &= \frac{\sum_{w,s,i} \mathrm{u}_{w,s,i} + m^{\mathrm{amb}}}{m}.
\end{aligned}$$

5.5 Econometric analysis

In this section, we analyze our data set to quantify UCPED and investigate the proactive prevention options within store operations. We commence by examining the variables used in our analysis, as presented in Section 5.5.1, followed by an overview of descriptive statistics outlined in Section 5.5.2. Afterward, we shift our focus to the discussion of hierarchical generalized linear modeling (HGLM) in Section 5.5.3, which serves as our chosen method for modeling UCPED.

5.5.1 Variables for analysis

The variables are derived from the exploratory analysis in Section 5.3. Each product has its characteristics. Moreover, identical items are stored differently on the shelves in each store (options (i)–(iv)), and the inventory composition (options (v)–(vii)) changes between each observation. We need to consider these item characteristics, the shelf settings in stores, and the replenishment-related effects, as well as their interdependence within our analysis. This necessitates the definition of variables on three different levels. More precisely, we consider (I) variables depending on the item, the store, and the inventory situation (*inventory level*), (II) variables depending on both store shelves and item characteristics (*store level*), and finally, (III) variables solely depending on the item characteristics (*item level*). Table 5.3

summarizes all variables considered across the three levels. Following our definition of UCPED, we define the binary variable $u_{w,s,i}$ as target variable, indicating if a shelf withdrawal w in store s of item i constituted a FEFO violation.

Target variable	
$u_{w,s,i}$	Binary variable; indicating if a customer withdrawal w in store s for item i is classified as undesired customer picking for ED
(I) Inventory-level variables	
$\text{Avail.Inventory}_{w,s,i}$	Total available number of stock units on withdrawal w in store s for item i
$\text{Min.RSL}_{w,s,i}$	Remaining shelf life of the first-to-expire product on withdrawal w in store s for item i
$\text{EDVariety}_{w,s,i}$	Number of distinct expiration dates on withdrawal w in store s for item i
(II) Store-level variables	
$\text{ShelfLevel}_{s,i}$	Categorical variable; describing the vertical shelf level allocation in store s for item i
$\text{Cardboard}_{s,i}$	Binary variable; indicating whether store s presents item i in a cardboard box or not
$\text{GrabbingSpace}_{s,i}$	Ordinal variable; assessing the available space to reach back row in store s for item i
$\text{ShelfSpace}_{s,i}$	Shelf space assigned in store s to item i
(III) Item-level variables	
Branded_i	Binary variable; indicating whether item i is a branded product or not
CasePackSize_i	Number of sales units in one case pack of item i
EDVisibility_i	Binary variable; indicating whether the ED label is printed on top of item i or not

Table 5.3: Overview of variables and hierarchical structure of variables

(I) Inventory-level variables Inventory-level variables concern the inventory composition observed of item i at the store s on withdrawal w. The inventory level describes the time-dependent changes between two observations due to store replenishment and customer withdrawal and includes three variables: the available inventory ($\text{Avail.Inventory}_{w,s,i}$; representing option (v), measured in stock units), the minimum remaining shelf life ($\text{Min.RSL}_{w,s,i}$; representing option (vi) and measured in days), and the variety in the EDs ($\text{EDVariety}_{w,s,i}$; representing option (vii), indicating the number of available EDs). Please note that these variables describe the inventory situation (stocktaking) for all withdrawals between two consecutive observations due to the hourly data collection.

(II) Store-level variables The store-level variables relate to a specific shelf setting within each store s, indicating where and how an item i is positioned on the shelves. The store level describes the static, store-specific setting. We apply four store-level variables. The vertical shelf allocation is described by the categorical variable $\text{ShelfLevel}_{s,i}$ (related to option (i)). As we observed shelves with different heights, we distinguish four shelf levels: 'ankle', 'waist', 'eye', and 'top' level. For the product presentation (option (ii)), we introduce the binary variable $\text{Cardboard}_{s,i}$, indicating whether a product is presented in a cardboard box (= 1) or as a single unit on the shelf. The grabbing space (option (iii)) describes the available space to reach a back row item and is classified as 'loose', 'dense', and 'very dense' (see Section 5.3). The corresponding variable $\text{GrabbingSpace}_{s,i}$ is defined on an ordinal scale with a natural order. The variable $\text{ShelfSpace}_{s,i}$ (option (iv)) defines the number of facings of an item divided by the number of facings of an entire case pack. This is necessary as all units within one cardboard box carry the same ED. It is measured in case packs and includes all vertical and horizontal facings.

(III) Item-level variables The item level includes three variables that only concern the product itself. They are externally determined by the manufacturer and not in the retailer's sphere of influence. The binary variable Branded_i denotes whether an item is branded or a private label. As such, it is an indicator of the price level. The CasePackSize_i denotes the number of sales units bundled together in a case pack. Moreover, EDVisibility_i indicates whether the ED label is printed on top of the item and thus directly visible or if customers need to search for the label.

5.5.2 Descriptive statistics

Conditional data set Customer cannot pick without at least two different EDs. In the following, we refer to the conditional data set where this criteria is met. Table 5.4 presents the summary statistics of UCPED for all 14 product groups. We differentiate between UCPED$^{\text{approx}}$ for the approximate share, UCPED$^{\text{LB}}$ for the lower bound (LB) and UCPED$^{\text{UB}}$ for the upper bound (UB) (see Section 5.4.2). The average UCPED$^{\text{approx}}$ share is 29%, with a LB of 26% and an UB of 35%. In other words, at least every fourth and at most every third customer withdrawal violated FEFO. The UCPED shares vary across product groups. The product group most prone to picking is milk with an average UCPED$^{\text{approx}}$ share of 45% (UCPED$^{\text{LB}}$ = 38%, UCPED$^{\text{UB}}$ = 53%), and the lowest UCPED$^{\text{approx}}$ share was observed for vegetarian cold cuts with, on average, 4% (UCPED$^{\text{LB}}$ = 4%, UCPED$^{\text{UB}}$ = 12%). Results on an item level (see columns 5–7 in Table 5.4) indicate not only a difference between but also within product groups. For example, the delta between the milk product with the highest (*max*) and lowest (*min*) UCPED share is 33 percentage points (pp.) in our sample. Large deviations within product groups can also be found for salmon (35 pp.) and cold cuts (24 pp.). The average delta between the most and the least UCPED item within a product group is 17 pp. The substantial variability observed suggests that aggregating data at the product group level may not be a viable approach for subsequent analysis. Consequently, we opt to analyze each individual item independently.

	UCPED (per group)			UCPED$^{\text{approx}}$ per item i			Records[2]	
Product groups[1]	approx	LB	UB	*min*	*max*	Δ	n	m
Milk	0.45	0.38	0.53	0.25	0.58	0.33	376	1,005
Cream	0.36	0.33	0.42	0.23	0.40	0.17	548	1,855
Cream cheese	0.33	0.31	0.38	0.27	0.44	0.17	326	734
Buttermilk	0.33	0.30	0.39	0.25	0.39	0.14	175	310
Butter	0.29	0.27	0.32	0.16	0.31	0.15	457	1,669
Semi-hard cheese	0.29	0.26	0.36	0.28	0.29	0.01	330	717
Yoghurt (plain)	0.28	0.25	0.35	0.19	0.36	0.17	229	586
Mozzarella	0.26	0.23	0.32	0.19	0.36	0.17	520	1,809
Convenience pastries	0.24	0.22	0.29	0.12	0.30	0.18	267	469
Curd	0.24	0.21	0.30	0.10	0.30	0.20	320	726
Cold cuts	0.23	0.22	0.28	0.07	0.32	0.25	277	558
Salmon (fish)	0.22	0.19	0.31	0.08	0.43	0.35	223	443
Pudding (dessert)	0.16	0.15	0.24	0.15	0.20	0.05	221	470
Vegetarian cold cuts	0.04	0.04	0.12	0.03	0.06	0.03	139	236
All groups	0.29	0.26	0.35	0.03	0.58	0.17	4,408	11,587

[1] Product groups sorted by UCPED$^{\text{approx}}$ in descending order
[2] n = observations, m = withdrawn units

Table 5.4: Summary statistics of UCPED for product groups

Aggregated results over all items show differences in UCPED for selected options of the shelf design. Table 5.5 presents the summary statistics of UCPED for store-level variables. For top level allocations ($\text{UCPED}^{\text{approx}} = 0.17$), single unit refill ($\text{UCPED}^{\text{approx}} = 0.20$), very dense shelves ($\text{UCPED}^{\text{approx}} = 0.19$), and shelf space values ≤ 1 ($\text{UCPED}^{\text{approx}} = 0.20$) the average UCPED shares are noticeably below average. Results on a store level (see columns 6–8 in Table 5.5) indicate differences also between stores. For example, the average delta between the store with the highest (*max*) and the lowest (*min*) UCPED share for all products stored at ankle level is 31 pp. The differences between stores are expected as products are allocated differently across stores.

		UCPED			$\text{UCPED}^{\text{approx}}$ per store s			Records[1]	
Variables		approx	LB	UB	*min*	*max*	Δ	n	m
Shelf level	top	0.17	0.15	0.27	0.07	0.25	0.18	242	473
	eye	0.31	0.28	0.38	0.18	0.47	0.29	862	1,792
	waist	0.30	0.27	0.37	0.18	0.40	0.22	951	2,038
	ankle	0.29	0.27	0.35	0.14	0.45	0.31	2,353	7,284
Product presentation	cardboard	0.31	0.28	0.36	0.18	0.45	0.27	3,510	9,848
	single unit	0.20	0.18	0.29	0.14	0.28	0.14	898	1,739
Grabbing space	loose	0.31	0.28	0.36	0.16	0.45	0.29	1,098	3,344
	dense	0.31	0.28	0.37	0.18	0.47	0.29	2,467	6,592
	very dense	0.19	0.17	0.27	0.12	0.30	0.18	843	1,651
Shelf space	≤ 1	0.20	0.18	0.28	0.16	0.28	0.12	2,111	5,007
	$[1-2]$	0.36	0.33	0.42	0.17	0.52	0.35	1,598	4,646
	> 2	0.35	0.33	0.39	0.17	0.49	0.32	699	1,934

[1] n = observations, m = withdrawn units

Table 5.5: Summary statistics of UCPED for store-level variables

Data set for modeling approach We will first consider $\text{UCPED}^{\text{approx}}$ for the analysis to only consider shelf withdrawals that can be unambiguously classified in 'FEFO' or 'UCPED' ($m = 10,564$). The number of observations differs with the chosen approach to calculate the UCPED shares (for LB, UB: $m = 11,587$). Further, we scale and center all continuous predictor variables by the grand mean (see Enders and Tofighi, 2007). This standardization ensures that predictors are on the same scale, supports model convergence, and facilitates the interpretation of their effects. Table 5.6 shows the correlation among the variables. We observe no correlation higher than 0.7 and only one correlation that is higher than 0.5; namely the correlation between Avail.Inventory and CasePackSize. This relationship is expected as larger case packs induce higher inventories. Beyond that, there is no evidence of collinearity (see Shieh and Fouladi, 2003; Guyon and Elisseeff, 2003). We, therefore, continue our analysis with this set of variables.

Variable	Mean	(s.d.)	Min.	Max.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) UCPED^{approx}	0.29	(0.45)	0	1	–								
(2) Avail.Inventory	33.72	(25.59)	3	164	0.07^a	–							
(3) Min.RSL	22.62	(14.69)	0	73	-0.04^a	-0.03^b	–						
(4) EDVariety	2.21	(0.52)	2	7	0.26^a	0.16^a	-0.19^a	–					
(5) Cardboard	0.85	(0.35)	0	1	0.08^a	0.35^a	0.02^c	0.06^a	–				
(6) ShelfSpace	1.72	(0.99)	0.67	6.00	0.14^a	0.16^a	-0.03^b	0.17^a	0.21^a	–			
(7) Branded	0.33	0.47	0	1	0.05^a	-0.3^a	-0.01	0.05^a	-0.24^a	0.03^b	–		
(8) CasePackSize	16.70	10.05	4	40	-0.02	0.62^a	0.13^a	0.00	0.39^a	-0.27^a	-0.39^a	–	
(9) EDVisibility	0.40	0.49	0	1	0.06^a	-0.07^a	-0.39^a	0.10^a	0.18^a	0.04^a	-0.03^b	-0.19^a	–

^{a} $p < 0.001$; ^{b} $p < 0.01$; ^{c} $p < 0.05$. Conditional data set: $n = 4,408, m = 10,564$. (s.d.) = standard deviation

Table 5.6: Correlation matrix for target and predictor variables

5.5.3 Hierarchical generalized linear modeling

Our sample includes observations from 42 items in six stores. Observations within stores or from the same item tend to be more similar to each other than observations randomly sampled from the entire population. For example, in our context, we have items within stores and observations of items within stores. Observations from the same item or the same store lack independence due to the multilevel structure of our data. Therefore, we apply a HGLM to appropriately account for this nested structure. This approach is used to analyze variance in the target variable when the predictor variables are at different hierarchical levels (Raudenbush and Bryk, 2002). HGLM is a general framework and a well-established approach that has been used in similar settings (see, e.g., DeHoratius and Raman, 2008; Hartzel and Wood, 2017). The hierarchical structure of the model allows for estimations of both within-group (level-specific) and between-group (cross-level) relationships. It accounts for the shared variance in hierarchically structured data and the dependence of observations at different levels. Consequently, the approach entails estimating relationships or slopes between predictor variables and the target variable on individual levels (e.g., the inventory level) and using these to estimate outcomes at higher levels within the hierarchy (e.g., the store level).

Further, HGLM can deal with unbalanced data, which is important for our conditional data, as the number of observations drawn from each store ($n_{min}^{\text{store}} = 563$, $n_{max}^{\text{store}} = 950$) and item ($n_{min}^{\text{item}} = 37$, $n_{max}^{\text{item}} = 269$) vary. Within the framework of HGLM, we use a logit link to account for the dichotomous (binary) outcomes of our target variable. We estimate the undesired picking for the withdrawal w in store s for item i, yielding the variable $u_{w,s,i} = f(Y_{w,s,i})$, where $u_{w,s,i}|Y_{w,s,i} \sim Bernoulli(Y_{w,s,i})$, $Y_{w,s,i} = \mathbb{P}(u_{w,s,i} = 1)$, and f denotes the logit function. The logit link function is a mathematical transformation used in logistic regression to model the relationship between predictor variables and the log-odds of a binary outcome. While the probability and odds scales are nonlinear, the logit scale is linear and enables a linear regression. To prove the statistical fit, we conduct a likelihood ratio test and show an improvement of the HGLM over a logistic regression (see Table 5.A1 in the Appendix) (Luke, 2017).

Model development

We follow the stepwise approach suggested by Raudenbush and Bryk (2002) and first estimate the null model (denoted as Model 0 in Table 5.7) without level-wise predictor variables. The predictor variables are then included level by level (see Models 1-3) until we derive the full model.

Null model We first fit an unconditional model with three levels to our data. The null model (Model 0) partitions the variance in $f(Y_{w,s,i})$ into three normally distributed components: the variance between items, the variance between stores, and the residual variance.

$$f(Y_{w,s,i}) = \gamma_{0,0,0} + a_{0,0,i} + b_{0,s,i} + \epsilon_{w,s,i}. \tag{5.2}$$

$\gamma_{0,0,0}$ is a fixed intercept parameter. Further, $a_{0,0,i} \sim N(0, \tau_\beta)$ is the main random effect of an item, $b_{0,s,i} \sim N(0, \tau_\pi)$ the main random effect of a store, and $\epsilon_{w,s,i} \sim N(0, \sigma^2)$ accounts for the random effect of the withdrawal w in store s for item i. Finally, we define τ_β, τ_π and σ^2 as the within-group variances in $f(Y_{w,s,i})$ for items, stores and withdrawals, respectively.

Conditional models We introduce predictor variables stepwise to Model 0, starting with the inventory-level variables (Model 1), followed by store-level (Model 2) and item-level variables (Model 3). The hierarchical structure is as follows: variables of Model 1 are nested within the next hierarchical level of Model 2 and are impacted by store-level variables. The same logic applies to the hierarchy of Models 2 and 3. As the lowest hierarchical level, the inventory level comprises the following predictor variables: available inventory, minimum remaining shelf life, and ED variety pertaining to individual withdrawals (see Section 5.5.1). This results in Model 1 (see Equation (5.3)), where $\pi_{0,s,i}$ is the fixed intercept and $\pi_{1,s,i}, \pi_{2,s,i}$, and $\pi_{3,s,i}$ represent the first-level fixed slopes.

$$\begin{aligned} f(Y_{w,s,i}) = \pi_{0,s,i} &+ \pi_{1,s,i} \cdot \text{Avail.Inventory}_{w,s,i} \\ &+ \pi_{2,s,i} \cdot \text{Min.RSL}_{w,s,i} + \pi_{3,s,i} \cdot \text{EDVariety}_{w,s,i} + \epsilon_{w,s,i}. \end{aligned} \tag{5.3}$$

In the second level, the store level, we introduce predictor variables that vary between the shelf configurations of the stores but remain constant across individual withdrawals. We split categorical vertical shelf-level variables into dummy variables (superscript dum). $\text{GrabbingSpace}_{s,i}$ is defined as ordinal variable (superscript ord). This results in Equation (5.4) for Model 2, where $\beta_{0,0,i}$ denotes a second-level intercept, and $\beta_{0,1,i}, \ldots, \beta_{0,4,i}$ the fixed second-level slopes. The term $b_{0,s,i}$ accounts for the random effect of the store on the target variable.

$$\begin{aligned}\pi_{0,s,i} = \beta_{0,0,i} + \beta_{0,1,i} \cdot \text{ShelfLevel}^{\text{dum}}_{s,i} + \beta_{0,2,i} \cdot \text{Cardboard}_{s,i} \\ + \beta_{0,3,i} \cdot \text{GrabbingSpace}^{\text{ord}}_{s,i} + \beta_{0,4,i} \cdot \text{ShelfSpace}_{s,i} + b_{0,s,i}.\end{aligned} \tag{5.4}$$

On the item level as the final level, we introduce control variables that vary between items but remain constant across different stores and withdrawals. We control for item characteristics that might influence $f(Y_{w,s,i})$ but are not under the retailer's control. Model 3 is defined as follows:

$$\begin{aligned}\beta_{0,0,i} = \gamma_{0,0,0} + \gamma_{0,0,1} \cdot \text{Branded}_i + \gamma_{0,0,2} \cdot \text{CasePackSize}_i \\ + \gamma_{0,0,3} \cdot \text{EDVisibility}_i + a_{0,0,i}.\end{aligned} \tag{5.5}$$

In Equation (5.5), $\gamma_{0,0,0}$ represents the third-level random intercept, and $\gamma_{0,0,1}, \gamma_{0,0,2}$, and, $\gamma_{0,0,3}$ the fixed effects specific to item-level variables. Accompanying these, the term $a_{0,0,i}$ captures the random effect attributable to the unique characteristics of each item on the target variable.

Estimation results

Table 5.7 presents the results of the HGLM developed in Equations (5.2) to (5.5). We compute Models 0 to 3 using the statistic software R-4.3.1 and the lme4 package. In addition to the logit regression coefficients, we present the odds ratios visualized in Figure 5.A2 in the Appendix. Following Raudenbush and Bryk (2002), we obtain the variation at the different levels by dividing the variance of the respective level random effect of the null model (Model 0) by the total variance of all random effects. We find that 76% ($= \frac{3.29}{0.76+0.28+3.29}$) of the variance in $\text{u}^{\text{approx}}_{w,s,i}$ is across withdrawals w, 18% across stores s, and 6% across items i (Model 0, Table 5.7). The model significance is assessed by comparing the negative log-likelihood between two nested models (see Table 5.A2 in the Appendix). Because the results are generally stable from one model to the next, and our final model has the best fit, we focus on the results of Model 3 in the following.

	Model 0	Model 1	Model 2	Model 3
Fixed effect				
(Intercept)	-1.34 (0.11)***	-1.34 (0.14)***	-1.94 (0.23)***	-1.84 (0.28)***
Avail.Inventory		-0.03 (0.04)	-0.05 (0.04)	-0.06 (0.04)
Min.RSL		-0.42 (0.10)***	-0.40 (0.09)***	-0.42 (0.09)***
EDVariety		0.44 (0.03)***	0.44 (0.03)***	0.44 (0.03)***
ShelfLevel[eye]			0.77 (0.22)***	0.82 (0.23)***
ShelfLevel[top]			0.34 (0.33)	0.36 (0.33)
ShelfLevel[waist]			0.41 (0.19)*	0.42 (0.20)*
Cardboard			0.46 (0.20)*	0.49 (0.21)*
GrabbingSpace			-0.75 (0.18)***	-0.73 (0.18)***
ShelfSpace			0.25 (0.09)**	0.25 (0.09)**
Branded				0.20 (0.26)
CasePackSize				0.19 (0.19)
EDVisibility				-0.32 (0.26)
Variance of random effects				
Store ($b_{0,s,i}$)	0.76	0.62	0.50	0.50
Item ($a_{0,0,i}$)	0.28	0.62	0.44	0.41
Log Likelihood	-5,743	-5,591	-5,570	-5,568
Withdrawals	10,564	10,564	10,564	10,564

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Standard errors in parentheses.

The residual variance for logit models is $\pi^2/3$ per model assumption and is therefore not reported in this table.

Table 5.7: HGLM results for UCPED$^{\text{approx}}$

The intercept ($\pi_{0,s,i} = -1.84$) in our model represents the log-odds of the event of interest, namely, the probability that UCPED takes place with $\mathbb{P}(u_{w,s,i} = 1)$. To provide a clearer interpretation, this intercept can be understood as a relative odds ratio of $exp(-1.84) = 0.16$. This ratio implies that when all predictor variables in the model are held constant at their reference (baseline) levels, and all random effects are set to zero, the probability of UCPED taking place (with $\mathbb{P}(u_{w,s,i}) = 1$) is 13.7% $(0.16/(1+0.16))$. The reference levels (baseline) for the categorical predictor variables are specific categories that are chosen for comparison with the other categories of the same predictor variable. When a non-branded item with no directly visible ED is placed on the shelf at ankle level using a single unit presentation and a loose layout for the grabbing space, the probability that UCPED will take place is therefore 13.7%.

For categorical predictor variables, the coefficients represent the difference in log-odds of UCPED between each category and the baseline category. As for continuous predictor variables, the coefficient represent the change in log-odds of UCPED for a one-unit change in the continuous predictor. Notably, we standardized our continuous variables for this analysis, so one unit equals the standard deviation (s.d.) of the respective variable. Due to its non-linearity in terms of odds and probabilities, logistic regression cannot be interpreted in a linear manner. For the interpretation of log-odds, odd ratios and probabilities, we keep all other predictor variables and random effects constant to the baseline. All odd ratios associated with the analysis can be found in Figure 5.A2 in the Appendix.

We find significant effects on $u_{w,s,i}^{\text{approx}}$ for six of our seven variables and corresponding impact options derived. In detail, the results identify the minimum remaining shelf life (Min.RSL) as a fundamental factor. We observe that a longer remaining shelf life $Min.RSL$ is linked to decreasing UCPED ($\pi_{2,s,i} = -0.42,\ t = -4.578$). Thus, in reverse, UCPED increases with a decreasing remaining shelf life of the foremost item on the shelf. An one-unit increase in $Min.RSL$ (1 unit = 1 s.d. = 14.69 days) reduces the log-odds of UCPED by 0.42, and translates to a relative odds ratio of $exp(-0.42) = 0.65$. This leads to odds of 0.10 (0.65×0.16) and translates to a probability of 9.4%. In other words, an increase of the $Min.RSL$ by 14.69 days decreases the UCPED probability from 13.7% to 9.4% in our baseline case. In a similar vein, we can interpret the outcome for the ED Variety. Our results indicate that the $EDVariety$ is positively associated with UCPED ($\pi_{3,s,i} = 0.44,\ t = 13.147$). The more different EDs a customer can choose from, the higher the tendency to withdraw fresher items. An one-unit increase in $EDVariety$ increases the log-odds of UCPED by 0.44. Thus, in the baseline case, the UCPED odds ratio rises from 0.16 to 0.25, and the probability increases from 13.7% to 19.7% with an one-unit increase (1 unit = 1 s.d. = 0.52 EDs) in the ED variety.

For the vertical positioning of an item, we observe that $ShelfLevel[eye]$ is associated with a higher UCPED ($\beta_{0,1,i} = 0.82$, $t = 3.567$). The expected odds of UCPED for an item stored at eye level are $\exp(0.82) = 2.26$ times the odds of UCPED for an item stored at ankle level. This translates to an increase in the UCPED odds ratio from 0.16 to 0.36 and probability from 13.7% to 26.3%. We do also see a smaller, however still significant, effect for waist level allocations (increasing UCPED probability from 13.7% to 19.3%) but no effect for top level allocations. The product presentation impacts UCPED. The variable *Cardboard* is positively associated with UCPED ($\beta_{0,2,i} = 0.49,\ t = 2.337$). The expected odds of UCPED for an item replenished in a cardboard are $exp(0.49) = 1.63$ times the odds of UCPED for an item refilled as a single unit, which translates to an increase in UCPED odd ratio from 0.16 to 0.26 and probability from 13.7% to 20.5%. Further, results show that the space for customers to reach back in the shelf has a significant effect. For the *GrabbingSpace* we find a negative linear effect on UCPED ($\beta_{0,3,i} = -0.73,\ t = -4.073$). The expected odds of UCPED for a dense shelf option are $exp(-0.73) = 0.48$ times the odds of a loose storing option. This translates to a decrease in UCPED odds ratio from 0.16 to 0.08 and probability from 13.7% to 7.1%. Finally, the $ShelfSpace$ is associated with higher UCPED ($\beta_{0,4,i} = 0.25,\ t = 2.888$). A one-unit increase in the $ShelfSpace$ variable increases the log-odds of UCPED by 0.25. Thus, in the baseline case, the UCPED odd ratio rises from 0.16 to 0.21, and the probability increases from 13.7% to 17.0% with a one-unit increase (1 unit = 1 s.d. = 0.99) in shelf space.

No substantial impact is observed for the predictor variable $Avail.Inventory$. Likewise, the control variables $Branded$, $CasePackSize$, and $EDVisibility$ fail to demonstrate any notable effects.

Robustness checks

In this section, we present robustness checks conducted to strengthen our findings. Detailed analysis results are provided in the Appendix.

(i) Considering the LB and UB for UCPED Initially, we considered $\text{UCPED}^{\text{approx}}$ as the target variable for our model. That means that we limited our data sample to only withdrawals that can be distinctly classified in 'FEFO' or 'UCPED' ($m = 10,564$). As a robustness check, we attempt the same analysis, including the 'Ambiguous' withdrawals, and ran our models first with UCPED^{LB} and then with UCPED^{UB} as target variable ($m = 11,587$). The effects described in the results section turn out to be robust for the UCPED^{LB} estimation (see Table 5.A3 in the Appendix). The slight deviation in the UCPED^{UB} estimation can be explained by overestimating customer picking. Based on a likelihood ratio test, the model with UCPED^{UB} as the target variable performs significantly worse than the previous models (see Table 5.A4 in the Appendix).

(ii) Adding the product group as an additional level to the HGLM Even though we leveraged the product group for product selection and to present our summary statistics (see Table 5.4), we did not include it in the HGLM shown above. As a robustness check, we add an additional random effect for the product group to our model. We find that some of the variance initially allocated to the item-level is now associated with the product group (see Table 5.A5 in the Appendix). However, for the main effect, we achieve directionally the same results and confirm robustness for this manipulation.

(iii) Computing the HGLM without standardizing the predictor variables We standardized all continuous predictor variables by the grand mean. As a robustness check, we compute the HGLM without this standardization. The effects described in the results section turn out to be robust for this manipulation (see Table 5.A6 in the Appendix).

5.6 Discussion

This paper contributes by collecting missing ED data in grocery retail stores. Based on this novel field data, we are able to quantify the extent of undesirable customer picking and investigate store operations to mitigate it. In Section 5.6.1, we highlight the empirical findings, discuss the managerial implications, and elaborate on the contribution to literature. We will do this along four areas. The first area will discuss general findings and the quantification. The second part elaborates on the findings about shelf planning, whereas parts three and four discuss findings on replenishment options. Finally, Section 5.6.2 discusses limitations and future research.

5.6.1 Empirical findings and its implications

Quantification of undesirable customer picking We first highlight findings on an aggregated level to indicate the level of UCPED. We collect ED data in the field. This unique data set shows that, on average, at least every fourth ($UCPED^{LB} = 26\%$) and at most every third ($UCPED^{UB} = 35\%$) customer withdrawal undermines the retailer's intended FEFO sequence. On a product group level, these numbers deviate slightly. The UCPED rate is for the majority of the product groups (10 out of 14 groups) between 22% and 38%. The extent of UCPED is problematic for retailers as it results in disorganized shelves that not only look unpretty but also may discourage customers from purchasing. Moreover, it leaves products with short EDs on the shelf and increases the risk of food waste. Rearranging the shelves to the intended FEFO order becomes a necessary daily task for store employees. However, it increases the costs of store operations. Therefore, it is crucial for retailers to understand potential mitigation measures. We identify potential retailer options through interviews, company visits, and literature analysis. We observe six significant options that not only may impact the customers' ED attention but also reduce the undesirable picking.

The majority of current consumer studies investigate ED attention with surveys. To move from checking to actually choosing items with longer EDs, we collected evidence from the field. Besides Hansen et al. (2023), our paper presents the only empirical study to investigate customer withdrawing behavior in a real-world setting. We find that the share of UCPED in our sample is far below the stated ED attention. For example, while Tsiros and Heilman (2005) quantify the frequency of checking EDs at 93% for milk products, we reveal a UCPED share of less than half with 45% ($\text{UCPED}^{\text{LB}} = 38\%$, $\text{UCPED}^{\text{UB}} = 53\%$). We can conclude that ED attention cannot be equated with UCPED. The discrepancy between ED attention and UCPED might (at least partially) be explained by the retail setting customers encounter when making purchasing decisions (see also Hansen et al., 2023). While Hansen et al. (2023) focus on the effect of inventory rotation and dynamic discounts on customer choice, we investigate the retailers' options in store operations to mitigate UCPED. While discounting is a reactive (and costly) mitigation measure, we show proactive options by identifying the impact of the vertical shelf level, the product presentation, the grabbing space, the shelf space assignment, the remaining shelf life, and the ED variety on UCPED. Our results show that responsibility for managing UCPED lies not only on store employees but also on a corporate level where guidelines for shelf allocation and replenishment are defined.

Influence of shelf plans on customer search effort Search costs and ED visibility are attributed to impact the customer withdrawal (see, e.g., Harcar and Karakaya, 2005). The shelf design eases or complicates search and withdrawal. We find three indications that UCPED can be mitigated by increasing the ED search effort for customers. First, we see that both middle shelf levels, i.e., eye level and waist level, are positively associated with UCPED compared to the ankle level. This effect is anticipated, as customers can easily recognize and reach the desired items on these shelf levels without the necessity to bend or stretch. Second, the assigned shelf space and its number of facings also exhibit a positive effect on UCPED as it can simplify the picking process for customers. In this case, the customers can easily choose between different units in the front row. And third, as expected, the grabbing space is negatively associated with UCPED. We show that a very dense shelf allocation reduces UCPED as it increases the effort for customers to pick a back-row item. All together, shelf plans are very relevant for mitigation. Even though our empirical findings provide a clear indication of where UCPED happens, the managerial answer is more complex, as retailers need to consider the potential implications on demand and operations. For example, while middle shelf levels and larger shelf space are positively associated with UCPED, they are also levers to increase customer attention and stimulate sales (see, e.g., Chandon et al., 2009; Eisend, 2014). And, of course, the shelf levels prone to UCPED must also be filled with products. Further, a very dense grabbing space might decrease UCPED but at the same time increase the effort for shelf replenishment and thus increase costs. Therefore, retailers need to incorporate UCPED in shelf design and layout planning. They need to carefully balance demand effects, operational feasibility, costs, and the consequences of UCPED to determine the optimal shelf allocation for each product and find compromises. For example, products with a low number of facings and a higher minimum remaining shelf life may be situated on shelf levels that have a higher likelihood for UCPED. Furthermore, grabbing space at these levels may be reduced.

The focus of current literature lies in understanding customer and product attributes that drive ED attention. The surveys show that ED attention depends mainly on the visibility of the ED label at the product (e.g., Harcar and Karakaya, 2005), category experience (Tsiros and Heilman, 2005) and perceived quality risk of a product category (Tsiros and Heilman, 2005; Choi et al., 2022). These attributes are determined either by the manufacturer (e.g., size and location of ED label at product packaging) or are customer-specific. They are not under the control of the retailer. We show that the ED attention is not only affected by the ED visibility, i.e., the printed label on the package, but also by how difficult it is to search for the ED and how the product can be retrieved. This relates also to findings of Shah and Hall-Phillips (2018). They indicate that time pressure during shopping negatively impacts ED attention.

Our findings also have implications for shelf space models as we provide an empirical foundation for the UCPED. Our results indicate that UCPED is influenced by so far not considered options in shelf design. Future shelf modeling approaches should consider the customer withdrawal behavior dependent on the effort customers encounter in picking a fresher product. In particular, the shelf space planning literature, where the inclusion of withdrawal behavior is still limited (see Bianchi-Aguiar et al., 2021; Riesenegger et al., 2023), can leverage our results to determine the optimal shelf allocation for a product.

Impact of remaining shelf life on quality risk perception The product quality risk is attributed to be a main driver for ED attention (Tsiros and Heilman, 2005; Harcar and Karakaya, 2005; Choi et al., 2022). Although this factor is in the literature related to the product category level, we are additionally able to establish a quality risk effect arising from retail operations. Our estimation results in Table 5.7 show that UCPED increases with a decreasing remaining shelf life of the foremost item on the shelf. To overcome the drawback of the logit scale in terms of interpretability, we calculate the average marginal predicted probabilities for our entire sample (in the following referred to as 'predicted probabilities') (see Agresti, 2002; Ai and Norton, 2003). While the effects and probabilities described in Section 5.5.3 are conditional on other predictors and random effects, the predicted probabilities presented in Figure 5.4 present the average change in probability across all other predictors and random effects. Figure 5.4a visualizes an almost linearly increasing probability for UCPED with decreasing remaining shelf life.

The relationship between minimum remaining shelf life and UCPED has implications for retailers. The closer the ED of a product, the more it is prone to UCPED. To manage this issue, it is essential to note that

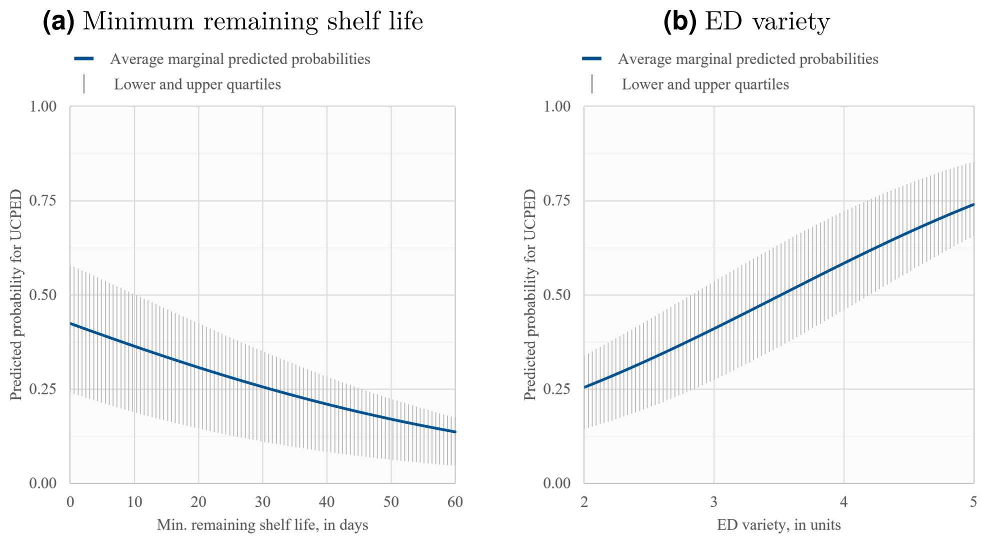

Figure 5.4: Predicted probabilities for UCPED$^{\text{approx}}$

the minimum remaining shelf life results from the product characteristics and the efficiency of operations. Close-to-expire products require special attention in shelf operations as customers will rummage within the shelves. Further, it is important to minimize throughput times from the supplier to the shelf to ensure the maximum possible remaining shelf life upon arrival at stores. As UCPED has negative consequences and rearranging the inventory is costly, retailers should prioritize products for frequent inventory rotation and train employees to increase awareness of the issue.

The UCPED increases with a lower minimum remaining shelf life. Albeit tested in a different setting, this is in line with literature on ED attention, which also increases with lower shelf life (see Harcar and Karakaya, 2005; Choi et al., 2022). Furthermore, Hansen et al. (2023) and Theotokis et al. (2012) indicate a lower willingness-to-pay for close-to-expire products. Tsiros and Heilman (2005) see category experience and the product quality risk as influencing factors for ED attention. They ascribe the differences between product groups to the perceived product quality risk allocated to them. Our results indicate that only a small proportion of the variance in UCPED is associated with the item. We show that 76% of the variance in UCPED is across withdrawals, 18% across stores, and 6% across items (see Model 0, Table 5.7 in Section 5.5.3).

Impact of ED variety on customer choice Interestingly, the inventory level and high availability did not impact the UCPED, whereas the ED variety is a significant driver for UCPED. Figure 5.4b visualizes an almost linearly increasing probability for UCPED with increasing ED variety. While for two different EDs, the predicted UCPED probability is, on average, 25%, it increases up to 75% with four EDs on the shelf. Based on these results, we can assume that customers recognize different EDs on the shelf and make use of this picking opportunity. The effect of product presentation in a cardboard also goes in this direction. Retailers should prevent ED accumulation, requiring more comprehensive processes. However, they push fresh products into the store before the old inventory is completely sold to ensure on-shelf availability. Our findings suggest that besides focusing on availability, retailers should actively manage the amount of different EDs on the shelf. This can be done, for example, with a lower replenishment frequency of stores and shelves (so that fewer EDs are mixed). This requires strict FEFO replenishment from distribution centers but also a total cost analysis to solve the trade-off between high replenishment frequency and lower out-of-stock risks. As ED information is not available in the replenishment system, the store is the earliest point when an ED accumulation can be recognized. Hence, as long as the inventory level still satisfies the expected demand, store employees may hold back batches with new EDs in the backroom storage and refill the shelf later in time. However, the costs for this additional process step need to be considered.

In line with Hansen et al. (2023), our findings indicate that a majority of customers still withdraw the foremost item from the shelf, even though a fresher one (from the back) is available. However, the ED variety increases

UCPED. These findings have implications for the replenishment literature. The models need not only differentiate between FEFO/LEFO withdrawals but also consider the positive effect of large ED variety on UCPED. In summary, we show that the currently applied fixed FEFO/LEFO ratios are not sufficient for simulating a real-world grocery retail setting. Future modeling approaches should consider the customer withdrawing behavior dependent on the remaining shelf life of the foremost product, the ED variety, and the effort customers encounter in picking a fresher product.

5.6.2 Limitations and future areas of research

Limitations of the study Due to the absence of ED information in scanner data, we collected data manually by periodic stocktaking to obtain the first insights into customer picking. There are some limitations to this approach. First, our research was conducted as a snapshot in time, focusing on a single retailer. Even though we cooperated with a leading European grocery retailer and ensured selecting a representative period, this limits our ability to generalize our results for the retail industry and analyze long-term patterns in UCPED. Second, we did not observe the withdrawal sequence itself, resulting in some sequence ambiguity associated with our collection approach. However, only 9% of our observations are affected, and we control for the effect of the ambiguity by also considering the lower and upper bound of UCPED. Third, we lack information about the individual customers involved in the item withdrawal. This absence of customer data hinders our ability to understand consumer intention behind their choices. Last, we reorganized the shelves in a FEFO logic once an hour to reflect the retailer's intended policy. However, retail shelves might get disorganized over the course of the day. For example, if a customer removes a whole case pack from the back of the shelf and places it at the front. Hence, our data is limited to organized shelves and neglects the impact of exogenous interventions disorganizing the shelves.

Future areas of research The scope of our study is limited by design, which offers opportunities for future research. We conducted this study in cooperation with a full-range retailer headquartered in Germany. As customer behavior can be context-specific, future research could repeat our study in different settings and for different retail formats, e.g., considering discounters or hypermarkets, which address different customer segments. Further, future research could extend the scope to different product categories (e.g., fruits & vegetables) and more stores (e.g., to consider different store characteristics). As data is limited by the manual data collection required in this context, future research could also automate the data collection process, e.g., through cameras or modified barcodes, including ED information. This would facilitate investigations into time-related effects, such as seasonality or the influence of closures. Exploring further mitigation measures for UCPED is also interesting, e.g., field experiments with communication strategies creating customer awareness for the negative consequences of UCPED. Even though we revealed retailers' options in store operations to mitigate UCPED, future research is needed to investigate the impact of those options on retail food waste. This would allow retailers to substantiate a profound cost/benefit analysis. Finally, future studies should extend the scope to the household level and also quantify the impact of customer picking on food waste at the consumer stage.

Appendix

Data collection process

Product group	Milk						Cream						Yoghurt (plain)					
Product name	Product 1		Product 2		Product 3		Product 1		Product 2		Product 3		Product 1		Product 2		Product 3	
SKU number	2228319		2865690		5494800		64840		8444108		5268729		5356784		1144899		1998141	
	Error	no	Error	no	Error	no	Error	no	Error	no	Error	no	Error	no	Error	no	Error	no
Time	Expiration date	Quant.	Expiration date	Quant.	Expiration date	Quant.	Expiration date	Quant.	Expiration date	Quant.	Expiration date	Quant.	Expiration date	Quant.	Expiration date	Quant.	Expiration date	Quant.
from	28.11.21	3	30.11.21	16	15.11.21	2	28.11.21	39	10.12.21	17	23.11.21	1	3.12.21	21	2.12.21	1	30.11.21	16
8	29.11.21	19			17.11.21	12					27.11.21	10	6.12.21	20	10.12.21	5		
CET											2.12.21	18			12.12.21	6		
EDs | Inventory	**2**	**22**	**1**	**16**	**2**	**14**	**1**	**39**	**1**	**17**	**3**	**29**	**2**	**41**	**3**	**12**	**1**	**16**
from	28.11.21	3	30.11.21	16	15.11.21	2	28.11.21	34	10.12.21	17	23.11.21	1	3.12.21	21	2.12.21	1	30.11.21	16
9	29.11.21	19			17.11.21	12					27.11.21	9	6.12.21	20	10.12.21	5		
CET											2.12.21	18			12.12.21	6		
EDs | Inventory	**2**	**22**	**1**	**16**	**2**	**14**	**1**	**34**	**1**	**17**	**3**	**28**	**2**	**41**	**3**	**12**	**1**	**16**
from	28.11.21	1	30.11.21	13	15.11.21	2	28.11.21	32	10.12.21	15	23.11.21	1	3.12.21	21	10.12.21	4	30.11.21	16
10	29.11.21	16			17.11.21	12					27.11.21	8	6.12.21	20	12.12.21	5		
CET											2.12.21	18						
EDs | Inventory	**2**	**17**	**1**	**13**	**2**	**14**	**1**	**32**	**1**	**15**	**3**	**27**	**2**	**41**	**2**	**9**	**1**	**16**
from	28.11.21	1	30.11.21	13	15.11.21	2	28.11.21	29	10.12.21	15	23.11.21	1	3.12.21	21	10.12.21	3	30.11.21	12
11	29.11.21	16			17.11.21	12					27.11.21	6	6.12.21	20	12.12.21	5		
CET											2.12.21	18						
EDs | Inventory	**2**	**17**	**1**	**13**	**2**	**14**	**1**	**29**	**1**	**15**	**3**	**25**	**2**	**41**	**2**	**8**	**1**	**12**
from	28.11.21	1	30.11.21	13	15.11.21	2	28.11.21	88	10.12.21	15	23.11.21	1	3.12.21	21	10.12.21	1	30.11.21	12
12	29.11.21	16			17.11.21	12					27.11.21	6	6.12.21	20	12.12.21	4		
CET											2.12.21	18						
EDs | Inventory	**2**	**17**	**1**	**13**	**2**	**14**	**1**	**88**	**1**	**15**	**3**	**25**	**2**	**41**	**2**	**5**	**1**	**12**
from	28.11.21	1	30.11.21	13	15.11.21	2	28.11.21	86	10.12.21	14	23.11.21	1	3.12.21	21	12.12.21	2	30.11.21	12
13	29.11.21	16			17.11.21	12					27.11.21	5	6.12.21	20				
CET											2.12.21	18						

Figure 5.A1: Digitized data sheets for data collection (translated)

HGLM model fit

	npar	AIC	BIC	logLik	deviance	Chisq	Df	Pr(>Chisq)
GLM	15.00	12341.67	12450.65	-6155.84	12311.67			
HGLM	16.00	11168.80	11285.04	-5568.40	11136.80	1174.87	1.00	$< 2.2e-16^{***}$

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. HGLM computed as Model 4.

Table 5.A1: Likelihood ratio test for GLM vs. HGLM

	npar	AIC	BIC	logLik	deviance	Chisq	Df	Pr(>Chisq)
Model 1	3.00	11491.40	11513.20	-5742.70	11485.40			
Model 2	6.00	11193.87	11237.46	-5590.93	11181.87	303.54	3.00	$< 2.2e-16^{***}$
Model 3	13.00	11165.97	11260.42	-5569.98	11139.97	41.90	7.00	$5.438e-07^{***}$
Model 4	16.00	11168.80	11285.04	-5568.40	11136.80	3.17	3.00	0.3663

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

Table 5.A2: Likelihood ratio test for Model 1–4

HGLM model results

Each point on the plot represents the odds ratio estimate (= exp(coefficient)) for a predictor variable. The horizontal line through each point represents the confidence interval for the odds ratio estimate. If the confidence interval does not cross the vertical line at a value of 1, it suggests that there is a statistically significant association between the predictor variable and the outcome variable UCPED. The variable GrabbingSpace is defined on an ordinal scale with a natural order and, therefore, divided into a linear (GrabbingSpace.L) and quadratic (GrabbingSpace.Q) predictor.

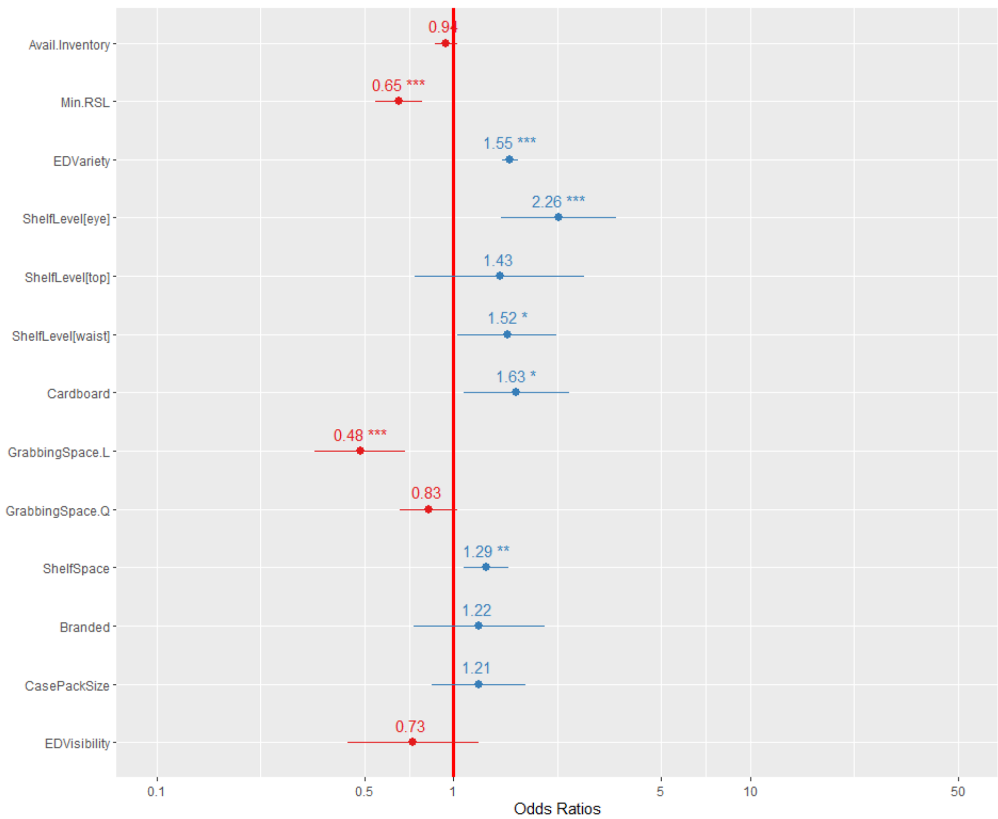

Figure 5.A2: Odds ratios for UCPED$^{\text{approx}}$ in the HGLM (Model 4)

Robustness checks

Robustness check (i) In this robustness check, we compute the HGLM with UCPED^{LB} and with UCPED^{UB} as target variable.

	Model 0	Model 1	Model 2	Model 3
Fixed effect				
(Intercept)	-1.48 (0.10)***	-1.43 (0.12)***	-2.01 (0.22)***	-1.96 (0.26)***
Avail.Inventory		0.05 (0.04)	0.03 (0.04)	0.03 (0.04)
Min.RSL		-0.33 (0.09)***	-0.33 (0.08)***	-0.35 (0.09)***
EDVariety		0.37 (0.03)***	0.36 (0.03)***	0.36 (0.03)***
ShelfLevel[eye]			0.75 (0.22)***	0.80 (0.22)***
ShelfLevel[top]			0.36 (0.32)	0.36 (0.33)
ShelfLevel[waist]			0.39 (0.19)*	0.39 (0.19)*
Cardboard			0.44 (0.20)*	0.47 (0.20)*
GrabbingSpace			-0.72 (0.17)***	-0.70 (0.17)***
ShelfSpace			0.27 (0.09)**	0.26 (0.09)**
Branded				0.19 (0.23)
CasePackSize				0.14 (0.17)
EDVisibility				-0.25 (0.23)
Variance of random effects				
Store	0.77	0.63	0.50	0.50
Item	0.22	0.44	0.32	0.30
Log Likelihood	-6,077	-5,950	-5,928	-5,927
Withdrawals	11,587	11,587	11,587	11,587

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Standard errors in parentheses.
The residual variance for logit models is $\pi^2/3$ per model assumption and is therefore not reported in this table.

Table 5.A3: Robustness check (i) – HGLM results for UCPED^{LB}

	Model 0	Model 1	Model 2	Model 3
Fixed effect				
(Intercept)	-0.85 (0.09)***	-0.92 (0.11)***	-1.37 (0.19)***	-1.31 (0.22)***
Avail.Inventory		-0.21 (0.04)***	-0.22 (0.04)***	-0.23 (0.04)***
Min.RSL		-0.37 (0.08)***	-0.35 (0.08)***	-0.37 (0.08)***
EDVariety		0.46 (0.03)***	0.46 (0.03)***	0.46 (0.03)***
ShelfLevel[eye]			0.57 (0.19)**	0.60 (0.19)**
ShelfLevel[top]			0.29 (0.27)	0.30 (0.27)
ShelfLevel[waist]			0.27 (0.16)	0.27 (0.16)
Cardboard			0.33 (0.16)*	0.34 (0.17)*
GrabbingSpace			-0.56 (0.15)***	-0.53 (0.15)***
ShelfSpace			0.11 (0.07)	0.11 (0.07)
Branded				0.20 (0.21)
CasePackSize				0.17 (0.15)
EDVisibility				-0.21 (0.21)
Variance of random effects				
Store	0.47	0.40	0.35	0.35
Item	0.19	0.41	0.29	0.28
Log Likelihood	-7,002	-6,820	-6,806	-6,804
Withdrawals	11,587	11,587	11,587	11,587

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Standard errors in parentheses.
The residual variance for logit models is $\pi^2/3$ per model assumption and is therefore not reported in this table.

Table 5.A4: Robustness check (i) – HGLM results for UCPED^{UB}

Robustness check (ii) In this robustness check, we add an additional random effect for the product group to our model.

	Model 0	Model 1	Model 2	Model 3
Fixed effect				
(Intercept)	-1.36 (0.16)***	-1.35 (0.21)***	-1.93 (0.26)***	-1.77 (0.29)***
Avail.Inventory		-0.03 (0.04)	-0.05 (0.04)	-0.05 (0.04)
Min.RSL		-0.45 (0.10)***	-0.44 (0.09)***	-0.47 (0.09)***
EDVariety		0.44 (0.03)***	0.43 (0.03)***	0.43 (0.03)***
ShelfLevel[eye]			0.77 (0.22)***	0.80 (0.22)***
ShelfLevel[top]			0.27 (0.33)	0.28 (0.34)
ShelfLevel[waist]			0.35 (0.19)	0.33 (0.20)
Cardboard			0.46 (0.20)*	0.46 (0.21)*
GrabbingSpace			-0.72 (0.18)***	-0.67 (0.18)***
ShelfSpace			0.24 (0.09)**	0.27 (0.09)**
Branded				0.19 (0.22)
CasePackSize				0.29 (0.16)
EDVisibility				-0.27 (0.27)
Variance of random effects				
Store	0.77	0.63	0.50	0.50
ProductGroup	0.27	0.47	0.28	0.30
Item	0.05	0.21	0.20	0.15
Log Likelihood	-5,738	-5,585	-5,566	-5,564
Withdrawals	10,564	10,564	10,564	10,564

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Standard errors in parentheses.
The residual variance for logit models is $\pi^2/3$ per model assumption and is therefore not reported in this table.

Table 5.A5: Robustness check (ii) – HGLM results for UCPED$^{\text{approx}}$

Robustness check (iii) In this robustness check, we compute the HGLM without standardization of the continuous predictor variables.

	Model 0	Model 1	Model 2	Model 3
Fixed effect				
(Intercept)	-1.34 (0.11)***	-2.41 (0.27)***	-3.45 (0.32)***	-3.61 (0.42)***
Avail.Inventory		-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
Min.RSL		-0.03 (0.01)***	-0.03 (0.01)***	-0.03 (0.01)***
EDVariety		0.82 (0.06)***	0.81 (0.06)***	0.81 (0.06)***
ShelfLevel[eye]			0.77 (0.22)***	0.81 (0.23)***
ShelfLevel[top]			0.34 (0.33)	0.35 (0.33)
ShelfLevel[waist]			0.41 (0.19)*	0.41 (0.20)*
Cardboard			0.46 (0.20)*	0.48 (0.21)*
GrabbingSpace			-0.75 (0.18)***	-0.73 (0.18)***
ShelfSpace			0.25 (0.09)**	0.25 (0.09)**
Branded				0.19 (0.26)
CasePackSize				0.02 (0.02)
EDVisibility				-0.32 (0.26)
Variance of random effects				
Store	0.76	0.62	0.50	0.50
Item	0.28	0.62	0.44	0.41
Log Likelihood	-5,743	-5,591	-5,570	-5,568
Withdrawals	10,564	10,564	10,564	10,564

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Standard errors in parentheses.
The residual variance for logit models is $\pi^2/3$ per model assumption and is therefore not reported in this table.

Table 5.A6: Robustness check (iii) – HGLM results for UCPED$^{\text{approx}}$

6 Conclusion and outlook

This doctoral thesis deals with options for food waste prevention in grocery retail. While Chapter 3 takes a broader perspective on food waste prevention options, Chapter 4 and Chapter 5 focus in particular on the customer withdrawal behavior and options within the scope of retail operations to mitigate it. The findings serve as a valuable resource for both practitioners and researchers aiming to prevent food waste at the retail stage. This chapter concludes the thesis by synthesizing the findings for each contribution individually and on an aggregated level. Additionally, future areas of research are summarized in the following.

6.1 Summary of findings and contributions

The detrimental impact of food waste on society, economy, and ecology has been widely acknowledged for quite some time. However, food waste still occurs at alarming rates globally. As **retail has a pivotal role in connecting supply and demand**, it is indispensable to identify and work on options to minimize food waste in grocery retail.

The retail industry has long accepted food waste as an unavoidable aspect of its operations. Increasing assortments and overstocked shelves were seen as value propositions and sales opportunities. Even though the culture is now changing towards a more sustainable approach, **grocery retailers are still in a dilemma.** They have to balance between satisfying customer expectations and the risk of food surplus deteriorating on the shelves over time. Resolving this trade-off is particularly challenging for perishable and highly perishable products.

Predominant strategies identified in current retail practice and literature are reactive options at the store level. Those mitigate the consequences once a food surplus has emerged but do not tackle the underlying causes. Thus, a **shift from reactive food waste reduction to proactive prevention** is required. Proactively preventing food surplus before it emerges is the more social, economic, and ecological option.

To begin, Chapter 3 investigates the *"how"* and *"why"* waste is minimized and establishes a framework for food waste prevention and reduction options within retail operations. In this way, propositions for proactive food waste prevention are derived from the empirical findings. Moreover, the implementation patterns can guide researchers and practitioners to prevention measures in inbound logistics, distribution & warehousing, and upstream store operations, which have not been intensively applied to date. It is highlighted that food waste prevention must also be addressed on a corporate level and should not only be left to store managers. This entails considering various facets, such as adopting a holistic cost perspective, aligning incentives, and sharpening competitive positioning.

Chapter 4 focuses on one such prevention option. Shelf merchandising is seen as highly impactful and is widely applied in retail practice. Even though retailers establish a FEFO shelf arrangement, self-service store customers can still rummage within the shelves to pick items from the back or from below to obtain products with a more distant ED. In fact, 45% of the retail food waste in the chilled assortment at our partner retailer is caused by customers violating the retailer's intended FEFO withdrawal sequence. Hence, customer picking for EDs is substantiated as a root cause of retail food waste. Furthermore, product-related drivers that may guide retailers toward critical products (e.g., short remaining shelf life and high turnover rates) and waste mitigation strategies (e.g., limiting the ED variety and application of ED-based pricing) are revealed.

Finally, in Chapter 5, the focus shifts to proactively mitigate customer picking within the scope of retail operations. Quantifying the extent of undesirable customer picking builds the empirical foundation. On average, at least every fourth (lower bound= 26%) and at most every third (upper bound = 35%) customer withdrawal violated the FEFO withdrawal sequence. Chapter 4 has shown that undesirable customer picking is problematic for retailers as it causes food waste. Therefore, proactive mitigation measures that a retailer can control are required. The analysis of the retail setting revealed options in shelf design (e.g., less grabbing space) and replenishment operations (e.g., availability of different EDs) to mitigate customer picking. To determine the optimal shelf allocation and replenishment strategy for each product, retailers need to carefully balance the implications of these options (e.g., demand effects, operational feasibility, costs) with the consequences of customer picking.

6.2 Future areas of research

The findings of this doctoral thesis open up additional research opportunities outlined in the following.

First, Chapter 3 has shown that the focus in the literature has been on reactive reduction options at the store level. The developed framework for food waste prevention and reduction options within retail operations can be leveraged to guide future research. The prevention measures in inbound logistics, distribution & warehousing, and upstream store operations, which have not been intensively applied to date, deserve more attention going forward. Dedicated studies on the effects of individual options and a detailed cost/benefit analysis would benefit retail practice.

Second, the method for customer picking waste identification developed in Chapter 4 can be adopted by scholars to replicate our study in diverse settings (e.g., retail formats) and across different assortments (e.g., ambient). Within this context, future research should investigate the connection between customer picking waste at the retail stage and household food waste. Holistic approaches examining the entirety of food waste are required.

Lastly, future research can also extend the scope of the study presented in Chapter 5. While Paper 3 focuses on retailers' options in store operations, exploring further customer picking mitigation measures connected to communication strategies and customer awareness might also be a promising research field. Further, an empirical foundation for modeling approaches incorporating withdrawal behavior is provided. The dependence of the customer withdrawal behavior on the remaining shelf life of the foremost product, the ED variety, and the effort customers encounter in picking a fresher product should be considered in future modeling approaches.

To summarize, mitigating food waste will remain a top priority for retailers. As grocery retailing is moving toward a more sustainable course of action, proactively preventing food surplus before it emerges will gain greater attention. This doctoral thesis has delivered valuable theoretical and practical insights to prevent food waste at the retail stage. It is crucial to recognize that besides the various options available to retailers, we, as customers, also play a substantial role in preventing food waste at the retail stage. So, before reaching for the freshest item on the shelf, it is essential to question whether it is truly necessary. Our mindful choices can make a difference in preventing food waste.

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Eidesstattliche Erklärung

Ich, Tobias Winkler, erkläre an Eides statt, dass ich die bei der promotionsführenden Einrichtung Campus Straubing für Biotechnologie und Nachhaltigkeit der TUM zur Promotionsprüfung vorgelegte Arbeit mit dem Titel: Food Waste Prevention Options in Grocery Retail am Lehrstuhl für Supply and Value Chain Management unter der Anleitung und Betreuung durch: Prof. Dr. Alexander Hübner ohne sonstige Hilfe erstellt und bei der Abfassung nur die gemäß § 7 Ab. 6 und 7 angegebenen Hilfsmittel benutzt habe.

☒ Ich habe keine Organisation eingeschaltet, die gegen Entgelt Betreuerinnen und Betreuer für die Anfertigung von Dissertationen sucht, oder die mir obliegenden Pflichten hinsichtlich der Prüfungsleistungen für mich ganz oder teilweise erledigt.

☒ Ich habe die Dissertation in dieser oder ähnlicher Form in keinem anderen Prüfungsverfahren als Prüfungsleistung vorgelegt.

☒ Teile der Dissertation wurden im International Journal of Physical Distribution & Logistics Management veröffentlicht.

☒ Ich habe den angestrebten Doktorgrad noch nicht erworben und bin nicht in einem früheren Promotionsverfahren für den angestrebten Doktorgrad endgültig gescheitert.

☐ Ich habe bereits am _____bei der Fakultät für _____der Hochschule _____unter Vorlage einer Dissertation mit dem Thema _____die Zulassung zur Promotion beantragt mit dem Ergebnis: _____

☒ Ich habe keine Kenntnis über ein strafrechtliches Ermittlungsverfahren in Bezug auf wissenschaftsbezogene Straftaten gegen mich oder eine rechtskräftige strafrechtliche Verurteilung mit Wissenschaftsbezug.

Die öffentlich zugängliche Promotionsordnung sowie die Richtlinien zur Sicherung guter wissenschaftlicher Praxis und für den Umgang mit wissenschaftlichem Fehlverhalten der TUM sind mir bekannt, insbesondere habe ich die Bedeutung von § 27 PromO (Nichtigkeit der Promotion) und § 28 PromO (Entzug des Doktorgrades) zur Kenntnis genommen. Ich bin mir der Konsequenzen einer falschen Eidesstattlichen Erklärung bewusst.

Mit der Aufnahme meiner personenbezogenen Daten in die Alumni-Daten bei der TUM bin ich einverstanden.

München, 29.11.2023

Ort, Datum

Unterschrift