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ORIGINAL PAPER

Improving supply chain planning for perishable food: data-driven implications for waste prevention

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Abstract

Waste in the perishable food supply chain is a challenge that data-driven forecasting methods can tackle. However, integrating such methods in supply chain planning requires development efforts. In this regard, understanding user expectations is the first development step. This study scrutinizes the expectations of a data-driven forecasting method for perishable food. The intended development is a joint initiative of a consortium containing three perishable grocery handling firms. Besides planning expectations, the study identifies and ranks demand-sensing factors that can enable data-driven forecasting for food waste prevention. As the participating firms compete in the same region, horizontal collaboration implications are additionally explored in this context. Accordingly, the study extracts relevant performance measures parallelized to food waste. A two-round Delphi study is used to collect the expectations from a data-driven forecasting method. Individual semi-structured interviews with experts from the initiative firms are conducted in the first Delphi round. Based on the extracted propositions in each interview, industrial experts jointly readdressed and ranked the extracted propositions in the second Delphi round, i.e., focus group workshop. The results reveal that the perishability characteristic emerges as a common expectation in linking supply chain planning with data-driven forecasting. This empirical study contributes to the research on supply chain forecasting and addresses the pertinent aspects of developing data-driven approaches to prevent food waste.

Keywords Food supply chain · Data-driven technology · Waste prevention

JEL Classification M110 · M150 · L660

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1 Introduction

Food waste is generated everywhere in the world. According to the United Nations Environment Programme (2021), supply chains generate 360 million tons of food waste yearly afore reaching households worldwide. Besides the resource exhaustion in the production phase (Foley et al. 2011), waste during food supply is an impactful environmental pollutant (FAO 2023). Furthermore, 690 million people in the world are hungry, and this number tends to increase by 2030 (WHO 2020). Alone in the European Union, food waste costs approximately 140 billion euros (Stenmarck et al. 2016). Holistically perceiving the affected dimensions, the best way to tackle the detrimental effects of food waste is to prevent it from happening (Papargyropoulou et al. 2014).

Due to their influence on end-consumer preferences and product flow in the supply chain, grocery markets are considered responsible for initiating interventions for food waste prevention (Gruber et al. 2016).

As end-consumer demand is challenging to be precisely predicted at a granular level that matches the perishable products' shelf life (Huber et al. 2017), demand uncertainty derives inflated supply quantities when tending to maximize product availability (Cachon and Terwiesch 2013). Therefore, their service performance is inventory level based (Hübner 2017).

Concurrently, food loss results from its operations during the transition in the supply chain (Teller et al. 2018). The profound relationship between produces limited shelf life and consumer freshness expectancy (James et al. 2006) constrain supply operations (Fikar et al. 2021).

These findings suggest that food waste is encouraged by demand and supply mismatch, being interlinked with product perishability attributes before reaching the consumption phase. The mismatch is sensitive to expected or occurring demand information, especially when considering the influence grocery markets have on end-consumer demand patterns due to promotions in a competitive setting (Krafft and Mantrala 2010).

To address this profound mismatch, data-driven forecasting methods have emerged as promising tools that can aid inventory management, and consequently minimize food waste. However, the successful integration of such data-driven forecasting methods into supply chain planning necessitates a deep understanding of user expectations. This understanding serves as the foundational step towards the development of data-driven technologies that can effectively prevent food waste in the perishable food supply chain.

An essential inquiry in grocery forecasting revolves around the effective collaboration and integration of data from various levels and participants within the supply chain (Fildes et al. 2022). Rather than sharing only orders, transparency in forecasted and occurring demand information upstream in a supply chain ensures synchronized operations and consequently reduces excess buffer inventory (Jonsson and Mattsson 2013). Such expected to be seamless information exchange is often case supported by a class of interorganizational information systems known as electronic data interchange (EDI) (Hill and

Scudder 2002; EDITEL 2021). Synchronizing supply chain operations based on transparent demand information is facilitated by well-known cooperation and collaboration platforms such as collaborative planning, forecasting, and replenishment (CPFR). CPFR is a consensus driven collaboration strategy. The buyer and vendor iteratively create a common business plan, generate the forecast, identify exception practices, i.e., promotions and judgmental adjustments, and finally decide on a replenishment policy (Danese 2007; Fliedner 2003).

Conversely, besides supplier-grocery relations, competitors also collaborate. Such horizontal collaboration, also known as coopetition, is defined as the dyadic relation of complementing and competing between firms that operate in the same environment (Nalebuff and Brandenburger 1997). In the grocery industry, coopetition is directed towards process standardization and logistic coordination. Process standardization covers the determination of efficient replenishment practices, ordering unit standardization, and data exchange novelties (Kotzab and Teller 2003). The goal is to provide end consumers efficient and sustainable offers and services. The efficient consumer response (ECR) is a neutral platform in Europe that organizes working groups with members from competing grocery merchants to discuss and determine best practices towards reaching a shared added value for the end-consumers (ECR 2023). Logistic coordination on the other hand exemplifies itself in purchasing communities. Exemplary in this regard, Hingley et al. (2011) evaluated the plausibility of fourth-party logistic initiatives to improve transportation aspects in a consortium of grocery retailers. Such can potentially play a role in sharing capabilities towards reaching a higher purchasing power. When considering innovations in coopetition, knowledge sharing is influenced by absorption capacity and appropriability (Ritala and Hurmelinna-Laukkanen 2013).

Besides implications from information and knowledge obtainable from vertical and horizontal collaboration, end-consumer demand forecasting accuracy, and consequently supply chain planning, is influenced by a vast amount of quantifiable external factors (Ali et al. 2009). In practice, many merchants consider a two-step base-times-lift approach to forecast demand (Cooper et al. 1999; Fildes et al. 2022). In the first step, a time series forecast is generated being followed by an adjustment step which includes judgmental aspects from any upcoming event, weather, promotions, and so forth (Fildes and Goodwin 2007). With the development of computational capabilities judgmental aspects can be integrated in the demand forecasting process via big data analytics (BDA) (Chehbi-Gamoura et al. 2020). BDA is defined as an application of methodologies to identify behavioral patterns in data that can be used to forecast future behavior (Shmueli and Koppius 2011). Different methodologies of the BDA stream on how external and judgmental factors are integrated in forecasting support systems (FSS) are available. Nevertheless, all the methods explicit the user expectation as a common challenge (Boone et al. 2019).

Addressing the impact of advancing the forecasting method therefore requires an expectation analysis. Under these premises, this work investigates the development initiation of a data-enriched forecasting system towards food waste prevention in grocery supply chains. Expectations from such a system are collected, classified, and interpreted based on a study containing 20 industry experts representing three grocery handling firms in Austria. Furthermore, potential demand-sensing features are extracted and prioritized. The prioritization of the features serves as a base to align the development efforts. Considering the profitable potential of preventing food losses (Papargyropoulou et al. 2014), this work elaborates on the trade-off between information absorption capacity and appropriability (Ritala and Hurmelinna-Laukkanen 2013) between grocery market competitors when salient external data are processed and made available by shared resources.

Based on the elaborated problem setting, this work tends to levitate the food waste prevention body of knowledge by contemplating the following research questions:

- What are the expected supply chain planning implications of introducing data-driven forecasting towards perishable food waste prevention?
- Which structural and functional requirements arise for the design of such a forecasting system?

Further on, the work elaborates on the impact an advancement in the forecasting system has on management decision-taking style by differentiating between the role of pure data-driven reliance and the human factor (Kache and Seuring 2017). To facilitate the study, a two-round Delphi study concluding with focus group workshops is deployed. The first round derives propositions from individual semi-structured interviews with all the participating experts. It focuses on planning advancement expectations from a data-enriched framework, identifying available factors as demand-sensing features, explores the expected role of coopetition, and further performance measures (PM) of interest parallelized with food waste prevention. The second round of the Delphi, i.e., the consensus round gathers all the experts in a focus group workshop. During the latter, discussions on the propositions extracted from the initial round take place and the forecasting system development guideline is agreed upon.

The remainder of the paper is structured as follows. Related literature is presented in the following section. Afterward, the methodology deployed is described in detail, followed by the findings and discussions. Summarized remarks, limitations, and future outlook conclude the paper.

2 Related literature

As a growing social and environmental concern, methods for preventing food waste are getting increased attention from researchers and practitioners. Supply chain planning developments i.e., replenishment and inventory planning for perishable products, are more thoroughly investigating empirically proven demand influences. Seasonality, quality, price, inventory level, vertical collaboration efforts, and investment schemes are some considerable predictors that capture demand behavior (Chaudhary et al. 2018). Yet, expectations from such planning frameworks remain not thoroughly capturable. To facilitate the research work, an outline is conducted regarding food waste and grocery supply operations, trends and perceptions for big data analytics, and current trends in applicable methods for external data-driven grocery retail forecasting.

2.1 Food waste and grocery supply operations

Operations management is a key success factor in the grocery industry, substantially impacting costs, profits, and service quality (Reiner et al. 2013). Yet, current practices described in the literature are to some extent perplexing when it comes to simultaneously tackling performance measures of different dimensions. The drivers of food waste in the brick-and-mortar grocery operations were mapped by many researchers. From case study research involving different retail store formats, Teller et al. (2018) identified and categorized the root causes of in-store food waste. In the current food deterioration setting, the limitation towards predicting consumer behavior is one of the main causes of food waste in all the grocery retail formats studied. Similarly, Akkas et al. (2018) identified planning aspects that drive food waste generation in the retailing setting by deploying a case study. Besides the minimum order quantity, the supply chain age was identified as a novel variable of interest, which is also influenced by the forecasting accuracy. By deploying a systematic literature review, de Moraes et al. (2020) summarized and categorized operations responsible for food waste in the supply chain based on the standard quality management fishbone. From the categories identified, the most frequent cause of food waste was inadequate demand forecasting as a planning input.

Measuring food waste as a form of awareness creation in a supply chain and household level is crucial (Aschemann-Witzel et al. 2017; Cicatiello and Franco 2020; Dora et al. 2020; Halloran et al. 2014; Teller et al. 2018). However, detailed information about its cause in the focal sources is barely recorded (Teller et al. 2018). Properly recording food waste requires extensive labor input, in which investments to ensure quality data are expected (Cicatiello and Franco 2020). Dora et al. (2020) highlight the importance of measuring food waste as a financial value. There, from case study research involving more than 47 food processing companies in Belgium, it was concluded that besides product defects, contracts in the supplier-retailer interface are an important cause of food loss and waste.

When considering food supply chains, the grocery market has a bargaining advantage over its suppliers due to its direct interface with the end consumer (Gruber et al. 2016). Additionally, grocery markets have a strong financial position due to supplier trade credit extensions, where the such are embraced also in the context of unfair trade practices (UTP) in Europe (Directive—EU 2019). Therefore, suppliers are usually willing to request collaboration as important information such as expecting and current sales data are supposed to be provided by the retail chain (Fliedner 2003). However, such a setting faces change when suppliers are focal for the retailer's category management due to the fear of opportunism (Morgan et al. 2007). Structured collaboration initiatives such as CPFR are often disregarded due to high costs associated with initiation (Fliedner 2003; Smith 2010; Whipple and Russell 2007). Nevertheless, investments in vertical collaborative-relation building prove to lower the transaction costs from assured transaction repetitiveness, shared knowledge creation, easing the information exchange safeguard, and investment in assets (Dyer 1997). Simultaneously, collaboration programs such as CPFR mitigate uncertainty, where minimizing the latters' impact is the main problem-solving objective in supply chain management (Reiner and Trcka 2004). CPFR is adapted by numerous players in the grocery industry (ECR 2023). However, the potential of extending collaboration frameworks explicitly towards the food waste prevention objective is unexplored.

From a logistics perspective, an overview on horizontal collaboration was conducted by Ferrell et al. (2020). Innovations in information sharing platforms were emphasized as future enablers of such initiatives. While focusing on grocery retailing operations, specifically the opportunities to coordinate imports for the grocery industry in UK, Sanchez Rodrigues et al. (2015) qualitatively explore the mediation of information sharing. Similarly, Hingley et al. (2011) elaborate on the enablers of grocery retailers to join a fourth party logistics initiative. The latter concluded that external forces that might compromise the current market value are the main incentive to overpass opportunistic behavior and commit to a horizontal collaboration scheme.

From the presented review findings, it can be inferred that demand forecasting and developing a clear waste estimation plays an important role when it comes to inventory management with prevention considerations. Furthermore, as information sharing is the main trigger of vertical and horizontal collaboration, and consequently planning advancement, they cannot be seen as independent in a supply chain. The indirect effect of other parties involved may result in higher profits or losses depending on their strategic alignment.

2.2 Big data analytics in grocery supply chain management

Compared to other hedging possibilities such as inventory and capacity management, forecasting is a direct lever to tackle uncertainty as a flexibility enabler i.e., efficient layout and process flow management (Kalchschmidt et al. 2010). Nevertheless, forecasting reliability is dependent on knowledge acquired from data (Hastie et al. 2009). From a comprehensive review on BDA in supply chain management, Roßmann et al. (2018) indicate that BDA can reduce information processing requirements and increase information processing capacity towards the reduction of uncertainty in supply chain operations. The availability of open-source external data helps to produce novel, high quality short-term forecasts (Talwar et al. 2021).

Considering price and quantity as demand drivers in the perishable grocery setting (Chaudhary et al. 2018), external data of a company can be internal data of another competing company (Ritala and Hurmelinna-Laukkanen 2013). This holds especially during promotional planning because it represents the grocery markets competitive advantage. Forecasting such periods is a challenge as prices are decided in the last minute and the manufacturer faces challenges when adjusting its capacity (Krafft and Mantrala 2010).

A review of current trends and developments in BDA in supply chain management is elaborated by Talwar et al. (2021) and Kache and Seuring (2017). Based on a deductive approach, the latter infer that the main challenges of integrating BDA in supply chain management remain governance and compliance followed by integration and collaboration. Yet, defining specific performance measures of interest, i.e., food waste prevention based on predictive and prescriptive analytics, is not overtly addressed in the investigated literature. From a review on data-driven agricultural supply chains, Kamble et al. (2020) point out that food waste is often times addressed on a descriptive setting i.e., on a life cycle assessment basis, and that prevention is the best way to mitigate its possible impact. However, the summarized approaches consider food waste as a postulate that can generate an added value, for example through valorization, rather than planning towards prevention. In this context, Belaud et al. (2019) develop a framework to evaluate valorization opportunities during the organic products lifecycle by deploying external data analytics. The developed framework points towards a boundary between decision support systems (DSS) and semi-automated decision making.

Within the family of decision support systems, FSS integrate managerial judgement with quantitative predictions to produce forecasts (Fildes et al. 2006; Hyndman and Athanasopoulos 2018). An essential aspect that is researched widely is the acceptance of DSS (Gönül et al. 2006). Aversion on algorithmic outputs (Burton et al. 2020, 2023; Mahmud et al. 2022) and automated feedback-loops for debiasing human judgements (Aruchunarasa and Perera 2023; Balla et al. 2023; Berger et al. 2021) are among the newer fields of research in the context of FSS, which prove the necessity to fulfill human-related acceptance criteria. In this context, data-driven decision making is defined as a practice to use data analysis instead of intuition for decision making. Brynjolfsson et al. (2011) demonstrate a positive correlation between company performance and the extent to which it operates data-driven.

From this part of the review, it can be inferred that BDA in grocery supply chains is drastically gaining the research attention expected towards ensuring reliable forecasts that serve as a planning mechanism. Yet, collaborative information sharing for forecasting, especially horizontally between the grocery handlers is a gap identified. This work tends to further extend the reviewed body of knowledge by exploring the BDA facilitated link between grocery supply chain operations and the risks associated with information exchange towards food waste prevention.

2.3 Applicable methods in data-driven grocery retail forecasting

In today's data-enriched planning environments, retail demand forecasts can be fed by multiple factors using different methods. A comprehensive mapping of methods developed, and factors used for forecasting retail demand is elaborated by Fildes et al. (2022). On a product level, three dimensions are distinguished to characterize retail demand forecasting to serve in supply planning: time granularity, product hierarchy, and position in the supply chain. Goltsos et al. (2022) present a review of forecasting methods with a specific focus on inventory planning implications. The authors differentiate the forms of integrating replenishment policies with forecasting methods. An essential aspect of demand forecasting is the adjustment made based on the forecaster's judgment. In that regard, Fildes and Goodwin (2007) listed the essential judgmental adjustments from empirical research including 149 forecasters. Promotions, price changes, holidays, regulations, and inventory insufficiencies were the top listed adjustment reasons. Based on regression analysis, van Donselaar et al. (2016) identified price discount, in-store display, product position on the promotion leaflet, holidays, and substitutability as the most influencing factors of perishable product demand during a promotion period. The proper distinguishment of promotion elements, i.e., systematic events, was also evaluated as a positive correlator of demand in the study by Abolghasemi et al. (2020b). Importantly to note is that promotion performance is product category mix driven. In this regard, Reutterer et al. (2017) present a framework that considers historical purchasing patterns to facilitate the bundling of product categories in a promotion plan to increase their target marketing efforts.

Existing solutions offer a range of potential methods (Di Pillo et al. 2016; Liu and Ichise 2017; Tiainen 2021). Hybrid methods constitute a promising way to ensure trust and explainability of the forecasting system. Time and day-related features, like holidays, weekdays, and seasons, are employed by Çetinkaya and Erdal (2019), Liu and Ichise (2017), or Tiainen (2021). Mobile transactional data is suggested in the agri-food supply chain as an enabler for new opportunities in big data analytics (Protopop and Shanoyan 2016) but has not yet been used in perishable food demand forecasting.

Exemplarily, Sroginis et al. (2023) present an interface-driven integration of judgmental aspects in promotion period forecasting. The authors identify that the misinterpretation of contextual statements remains challenging when properly adjusting the forecast procedure. Considering weather as a demand influencer, Rose and Dolega (2022) developed a random forest model to quantify its impact on potential demand realization. Wind, temperature, humidity, and precipitation were used for different seasons to quantify the weather impact. Differentiating between regions where stores are located, the findings indicate that sales variance in urban areas, i.e., high streets, compared to rural areas, are substantially better explained by weather variables. Sillanpää and Liesiö (2018) developed a simplified forecasting approach considering weekday seasonality and intermittent nominal demand realizations. The authors argue that prediction densities as forecasting outputs are more suitable for inventory and workforce planning. The same is argued by Fildes et al. (2022) and Goltsos et al. (2022).

Prediction densities provide a range of possible outcomes, allowing retailers to make informed decisions based on the likelihood of different demand scenarios, especially considering that planners can analytically calculate the safety stocks based on forecasting quantiles. Even though the literature prevails on advancing point-forecast approaches, more emerging methods consider forecast distribution, intervals, and quantiles as outputs. In this regard, Fildes et al. (2022) argue that machine-learning approaches rarely provide interval or density forecasts.

Nevertheless, the judgmental adjustment of the forecasted quantities is unexplored in range-based outputs. The forecasting stream in retailing is driven by the tendency to capture judgmental adjustments of planners. Even if advanced forecasting methodologies are being deployed in the industry, the impossibility of constantly obtaining high-quality input data obligates the human factor to intervene (Khosrowabadi et al. 2022). Developments in integrating multiple external factors simultaneously in a FSS must consider the possibility of adjusting, i.e., appropriate the planning interface. Furthermore, research on integrating adjustments when shifting the forecasting output from a point toward a distribution, interval, or quantile is highly relevant in inventory planning.

3 Methodology

3.1 Suitability and design of the two-round Delphi study

When new phenomena are under investigation where little information exists, the Delphi method is suitable for gaining new insights (Rowe et al. 1991). Especially where long-term and technological change is projected, this method has been applied in the context of supply chain management (SCM) (Rowe and Wright 1999; Winkler et al. 2015). Delphi studies are a research method that involves gathering and synthesizing expert opinions on a particular topic or issue. They are often used to elicit expert opinions on complex or controversial issues. They can provide valuable insights into how experts view and understand a given topic (Boberg and Morris-Khoo 1992). In a two-round Delphi study, the first round typically involves conducting a series of semi-structured interviews with experts in the field. These interviews are based on open-ended questions designed to elicit expert opinions on the topic of interest. The second round of a two-round Delphi study involves organizing a focus group workshop to seek consensus on the extracted propositions. In this workshop, experts are invited to discuss and debate the propositions and to provide feedback and insights into their relevance and validity. Therefore, a two-round Delphi method is suitable in the context of this work.

This study applies the inductive approach to develop the theoretical fundament, followed by a deductive approach to develop the contextual relationship among the propositions extracted from the data (Allen 2017). The combined approach of using a Delphi study including inductive and deductive elements is widely used in the context of SCM, for example, by Wehrle et al. (2022), Roßmann et al. (2018), Sanchez Rodrigues et al. (2015), and Akkermans et al. (1999).

To approach the topic in a structured way and derive the pursued findings, the work distinguishes between two rounds of Delphi: formulating propositions and consensus-seeking. The systematic approach assures the validity and reliability of the results and is depicted in Fig. 1. In the pre-round, the current body of knowledge was surveyed, and a panel discussion of food retail and wholesale experts took place. On the one hand, this combined approach of identifying scientific foundations, and letting industry experts discuss from a practical perspective enabled the development of a substantial base for further investigation. From these perspectives, an inductive approach was used to derive the research questions for the questionnaire in the first Delphi round. The chosen perspectives also ensure that different sources for forming the questions were used, i.e., desk research, expert sessions, and brainstorming within the research team (Schmalz et al.

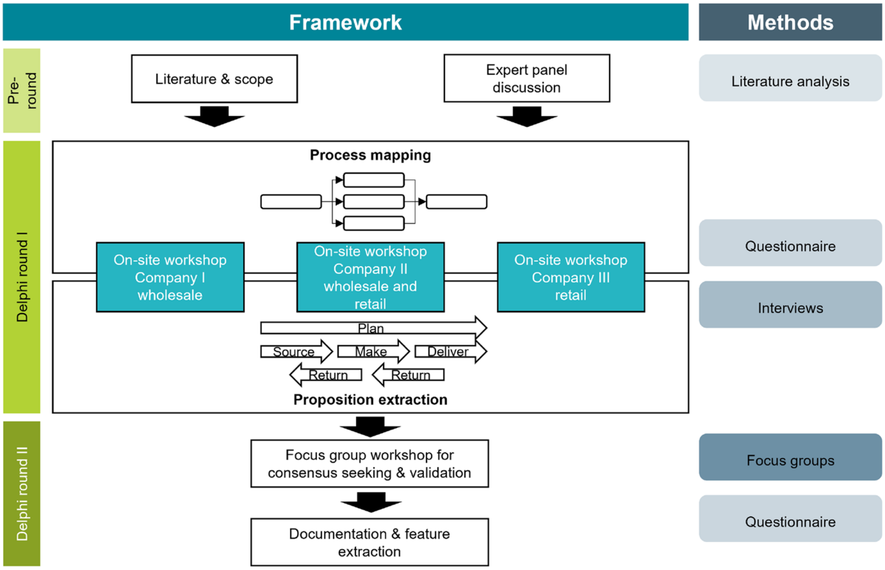

Fig. 1 Systematic research approach

2021). The findings are categorized according to their relevance to the topic and their probability of shaping future developments within the research field (Gausemeier et al. 1998).

In the first round of the Delphi study, the developed questionnaire was conducted with 20 experts in individual interviews for approximately 60 min each. The interview consisted of semi-structured questions, including leading and sub-questions, to guide the answers in the direction of the topic while leaving enough space for the interviewees to answer openly. Here, the emphasis lied on gaining insights into each stage according to the SCOR framework (Stadtler 2005). Current planning and forecasting procedures, replenishment policies, exception management practices, information flows, and organizational decision-making structures were asked. To induce practicality and guide the deductive categorization, the SCOR-model as a tool for analyzing supply chains was implied as an anchor to ensure consistency during the interviews. As defined by Stadtler et al. (2015), the first level of abstraction, namely the process types, was rephrased and explained before each interview:

- *Plan*—Covers supply capability and demand requirement matching, communication, and measuring supply chain performance.
- *Source*—Identification and selection of suppliers, contracts, and replenishment policies.
- *Make*—The process of transforming intermediate products to their final state—even though the investigated grocery markets focus solemnly on distribution activities, it was raised as a point to enlighten further suppliers' postponement and decoupling point opportunities (Jammernegg and Reiner 2007).

- *Deliver*—All steps needed for technical order management, warehouse management, and distribution, i.e., centralization versus direct store deliveries, reception of products, and further logistics activities.
- *Return*—Represents the current return policies to suppliers and post-delivery customer service.

A deductive coding approach enabled proposition extraction based on predefined topics. The interview material in the form of voice recordings and notes was transcribed and then analyzed with the software Nvivo (Nvivo 2023). The deduction of propositions from content analysis refers to identifying and testing hypotheses about a particular issue or topic through the analysis of data and documents. In proposition deduction from content analysis, researchers identify a set of propositions or hypotheses about a particular topic or issue and then use content analysis to test these propositions by examining the content of a given set of documents or data sources. This process involves coding and analyzing the content of the documents or data sources in order to identify patterns or trends that support or refute the propositions being tested. It can provide insights into how people communicate and interact and can help researchers better understand the underlying dynamics of social and cultural phenomena (Allen 2017).

The goals of the full-day expert session were twofold. On the one hand, to record and understand the processes within each company. On the other hand, to understand the dynamics within each department in more detail and investigate the expectations as and input of a facilitating tool towards food waste prevention. This workshop aims to reach a consensus on the extracted propositions and identify any areas of disagreement or uncertainty. The focus group workshop is typically structured to encourage open and constructive dialogue among the experts and may involve group discussions, breakout sessions, and structured exercises. The results of the focus group workshop are then analyzed and synthesized to produce a final set of propositions or recommendations for further research or action. These results can inform decision-making or policy development or guide further research on the topic of interest.

3.2 Research setting and sample selection

The three companies under investigation operate in both the food retail and wholesale industry. A brief description of the companies and number of respondents are enlisted in Table 1. In the context of this work, wholesale refers to specialized economic agents for supplying independent traders, the gastronomy sector, and large-scale events. Company I is a wholesaler with additional end-consumer shops with more than 95,000 employees in over 30 countries. Company II is domestically located in Austria and has elements from both retail and wholesale. With seven locations around the country, it employs 900 people and covers five different sales channels. Further on, company II differentiates itself from the rest of the companies based on its sourcing principles. To support regional sourcing and small and medium-sized enterprises (SME) working in the organic food branch, a platform for

Table 1 Description of participating companies

Type of company	Company description and relevance for the study	Number of interviewees
Food wholesaler (company I)	Wholesaler with more than 95,000 employees operating in over 30 countries worldwide	7
	Offers food deliveries to clients with own trucks and logistics service providers	
	Offers in-store purchase options for business customers	
Food wholesaler with retail stores (company II)	Company is domestically located in Austria and has elements from both retail and wholesale	7
	With seven locations around the country, it employs 900 people and covers five different sales channels	
	For supporting regional sourcing and SMEs working in the organic food branch, a platform for decentralized sourcing is active	
	Offers food deliveries to clients with own trucks	
	Offers in-store purchase options for business customers	
Food retailer (company III)	Mainly active in food retail directly to the end consumer, i.e., brick and mortar	6
	It operates in 48 countries worldwide and employs 410,000 people in over 13,500 stores	

decentralized sourcing is active, indicating that a vast amount of perishable products is regionally sourced. Company III is mainly active in food retail directly to the end consumer. It operates in 48 countries worldwide and employs 410,000 people in over 13,500 stores. As a focus of the expert sessions, complete supply chain coverage, including all relevant departments according to the SCOR framework, was ensured. This approach guaranteed that all relevant functions of the companies were covered, and findings could be mapped to all stages of the supply chain. The interviewed experts were chosen regarding their function and knowledge level within the company. More specifically, the interviewed respondents manage specific departments of interest, i.e., perishable product category management, operations management, IT infrastructure, procurement, quality assurance, and in-store auditing. Conclusively, respondents are epitheted as experts if they manage a business-responsible department in the affiliated company. In total, 20 respondents from three companies were interviewed.

3.3 Data collection

The initial questionnaire was developed based on the identified research gaps and stakeholder interests from the pre-round meetings. The leading questions were then refined to keep the first round of the interview as close to the topic as possible but simultaneously enabling to obtain open answers. This approach ensures the explorative nature of this work while covering the main topics. Table 2 summarizes the four resulting lead questions of the semi-structured interviews. For each of the questions, sub-questions were used to guide the answers. In the first question, the experts discussed how a forecasting tool with near real-time capabilities and consideration of external data could enable decisions for preventing food waste. In the second question they were asked, which additional influences and factors should be considered such that the forecasting tool has a positive effect. The third question addressed the subject of collaboration. Here, the experts were asked to what extent horizontal collaboration influences those factors regarding added value for clients. In the fourth question, the experts were asked for additional success factors, which would be impacted by an advanced forecasting tool.

3.4 Data validity

The validity of the methodology as well as the results obtained was ensured twofold. First, by following the systematic approach described in detail in Sect. 3.1. and second, by following the approach proposed by Yin (2009), see Table 3.

As Yin (2009) suggests, the validity of this qualitative research is evaluated based on the four dimensions of construct validity, internal validity, external validity, and reliability. The construct validity in the data collection and composition phase is ensured by the use of multiple sources of evidence as well as the establishment of a chain of evidence. Also, key informants, i.e., the experts, were informed of the results of each conducted Delphi round. The internal validity in the data analysis phase is maintained by logic models, i.e., the systematic approach and the used

Table 2 Semi-structured interview questions and sub-questions

Number	Question	Sub-questions
1	Considering the steps in the SCOR framework, how would a real-time SC and external data powered forecasting tool (increased forecasting accuracy) facilitate food waste mitigation decisions?	In a trade-off setting, what would be considered the benefits and negative influences of cohering data horizontally and vertically in the industry? (Lead towards the symmetric information in competition)
		What are the advantages and disadvantages from your department's point of view of sharing data along the supply chain?
		Where is this already the case today?
		What would be the future potentials?
2	What additional enablers can/should be worked on to improve the chance of such a tool being positive?	For example, structuring the reporting and communicating framework for enhanced decision making, S&OP
		Which areas of the company/supply chain would be improved in your view?
		Which areas of the company/supply chain would need to be improved to achieve the full benefit? E.g., internal reporting, procurement processes, planning processes, IT, etc.
3	What implications does horizontal collaboration have on such enablers towards the creation of an added consumer value? (For example, best practice sharing, setting a framework standard for the minimum order quantity, aligning service level expectations)	Do you use the ECR product categorization nomenclature?
		Are there any other examples of retailers working together either in the field of logistics or elsewhere? (Sharing distribution channels, case pack size determination)
4	Besides food waste mitigation, what would be the additional added value expected from real-time SC data cohering?	Besides food waste prevention, what performance measures would be of interest to be investigated in a data integration project?
		In addition to food waste prevention, what performance metrics should be examined as part of a data integration project?

Table 3 Evaluation of research quality based on Yin (2009)

Research stage	Quality test	Application within this paper
Data collection and analysis	Construct validity	The data collected stems from different sources as well as two rounds of the Delphi study, where 20 experts from the food retail industry were interviewed and a focus-group workshop undertaken.
		The data generated was confirmed during consecutive workshops by the experts.
		The results graphs and tables were presented to the experts for approval.
		The results were included in the joint project report including an opportunity to provide feedback.
Data analysis	Internal validity	The data analysis was conducted systematically based on the SCOR-framework.
		The propositions were extracted and condensed throughout internal project workshops and discussions.
		A cross-comparison of the responses between the stages of the Delphi study was conducted.
		The second Delphi round was used to verify the results of the first Delphi round.
Research design process	External validity	In the two stages of the Delphi study, 20 experts from three different companies participated in the study.
		The companies interviewed resemble over 50% market share of the Austrian food retail and wholesale market.
		A theoretical base was used to complement and structure data collection and analysis.
Data collection	Reliability	The two rounds of the Delphi study as well as the focus-group workshop were accompanied by a well-structured and prepared written protocol.
		The protocol was based on a theoretically-oriented literature review and practically-oriented expert discussion in the pre-round of the study.

SCOR-framework for pattern matching. External validity regarding the research design was assured by using the two-round Delphi approach, which is widely used and proven in existing literature on SCM. Last but not least, reliability in data collection of the study is provided by well-documented protocols in each stage of the study as well as an available and structured database.

The quality of the results was specifically ensured by a pre-briefing of the interviewees before each interview in the first Delphi round and a presentation of the results before the second Delphi round. The semi-structured interview questions including relevant sub-questions and a graphical and textual description of the SCOR model (APICS 2017) were sent to the interviewees in advance including a definition of the relevant terms and the procedure of the interview. In the pre-briefing at the beginning of the first round, the SCOR model and its components and terms were explained to the interviewees. The three levels process element level, configuration level, and top level and especially the emphasis on the top-level components plan, source, make, deliver, and return were explained. The interviewers additionally ensured quality by a semi-structured questionnaire, containing the four main questions and relevant sub-questions. The coverage of the sub-questions was tracked during the interview and helped to lead the answers back to the main topic in case of deviations. Also, the interviewee's respective company role, e.g., purchasing manager, logistics manager, etc. was classified in the context of the SCOR model and in connection with other functions of the company. Each interviewee signed a consent form with the knowledge, that the condensed results are used for publication purposes.

The features and performance measures Identified were derived based on a clustering in between the rounds and aligned with the existing literature. For a definition of the performance measures, the reader is referred to Table 4. Prior to the second Delphi round, the questionnaire was sent to the participants including the questions and performance measures to be ranked.

Before the start of the focus-group workshops of the second Delphi round, the interviewers introduced the session by recapitulating on the first round and presenting the condensed results. The results were presented, and their meaning in accordance with Table 4 explained to the experts. Here, the experts had the opportunity to clarify questions, adjust, and add additional relevant information to the results. By following this procedure, a common understanding of terms and definitions of performance measures could be reached among the experts.

Table 4 summarizes the relevant key performance indicators and their definition in accordance with existing literature and as extracted from the expert interviews. The performance measure *DSS recommendation acceptation quote as an automatization PM* was derived based on the prevailing literature on algorithm aversion in judgmental FSS (Burton et al. 2020, 2023; Mahmud et al. 2022). Here, the relatively new stream of including feedback-loops into such systems is of high relevance (Aruchunarasa and Perera 2023; Balla et al. 2023; Berger et al. 2021). The indicator *Environmental sustainability* primarily focuses on the main topic of the research project, namely food waste and its implications. The Food and Agriculture Organization of the United Nations further links food waste to carbon footprint and emphasizes the importance for environmental sustainability (FAO 2023). Another

Table 4 Definition of key performance indicators

Performance measure	Definition	Argumentation
Out-of-stock	The frequency or duration of products being unavailable for sale or out of inventory.	Performance indicator as defined in the basic literature, e.g. (Levy and Grewal 2023).
Product quality offered to end consumers	The level of excellence or satisfaction achieved by a product in meeting the expectations and needs of the end consumers.	Performance indicator as defined in the basic literature, e.g. (Besterfield et al. 1995).
Warehouse workflow day-to-day variance	The level of deviation or inconsistency in the day-to-day operations and processes within a warehouse, e.g., the fluctuations in efficiency, productivity, and accuracy of warehouse activities.	Performance measure extracted from the interviews of the first Delphi round.
DSS recommendation acceptation quote as an automatization PM	The percentage of recommendations generated by the system that are accepted and implemented by the users or decision-makers. The automated re-feeding of this information into the system.	Relevance revealed, among others, from Aruchunarasa and Perera (2023), Balla et al. (2023), and Berger et al. (2021). Performance measure extracted from the interviews of the first Delphi round.
Environmental sustainability	The environmental impact associated with food retail, including the food waste rate and Greenhouse Gas Emissions.	Performance measure extracted from the interviews of the first Delphi round. Literature on the effects of food waste on environmental sustainability factors, e.g., FAO (2023) and Marsden and Morley (2014).
Fair pricing from farm to fork	Equitable pricing practices throughout the entire food supply chain, ensuring fair compensation for farmers, producers, distributors, retailers, and consumers. The goal is to promote transparency, minimize exploitative pricing practices, and foster a sustainable and ethical food system that benefits all stakeholders involved.	Performance measure extracted from the interviews of the first Delphi round. Relevance to be found in e.g., Agafonow (2020), Simatupang and Sridharan (2002).
Staffing costs	The financial resources associated with employees, including the expenses associated with wages, salaries, benefits, and other related costs attributed to staffing.	Performance indicator as defined in the basic literature, e.g., Mathis et al. (2017).

Table 4 (continued)

Performance measure	Definition	Argumentation
Turnover for inventory held	Rate at which inventory is sold and replaced within a given period. It indicates the efficiency of inventory management and reflects the frequency with which inventory is replenished or turned over during a specific timeframe.	Performance indicator as defined in the basic literature, e.g., Stevenson et al. (2014).

performance indicator that needed clarification before the second Delphi round is *Fair pricing from farm to fork*, where the expert opinions and literature foundations were streamlined. Opportunistic behavior can result in increased price margins or costs within collaborative supply chains (Formentini and Romano 2016; Simatupang and Sridharan 2002). This apprehension was also present in the expert interviews especially in the context of cartel laws, which are monitored and executed strictly in horizontal collaboration in the retail domain. The remaining performance indicators in Table 4 are commonly known in the domain of food retail and wholesale and especially in logistics and supply chain management. They did not require major clarifications and definitions beyond the existing literature and expert knowledge.

4 Findings

4.1 Findings from the two-round Delphi study: propositions from semi-structured interviews

In the first round of the Delphi study, the propositions for relevant features for the planning system were identified. The second round of the Delphi study focused on consensus seeking within a focus group format. The following tables present the extracted propositions and consensus votes for the extracted propositions. Figure 2 shows expected planning facilitators from an advanced analytical tool. Figure 3 ranks the influences and factors as demand-sensing features, which have been proven necessary for a FSS by the domain experts. Figure 4 elaborates the results on the coopetition role, and Fig. 5 summarizes the discussions on further performance

First Delphi round								Second Delphi round
SCOR level	Proposition	Category Management n=2	In-Store Audit n=2	Management & IT Infrastructure n=8	Procurement & Distribution n=6	Product Quality Assurance n=2	Total (n=20)	Standard Deviation
Plan	P1) Serving as a synchronization framework with the perishable producer to maximize quality - Reduce products supply chain age	0	2	7	5	2	16	0,85
	P2) Awareness creation for possible hoarding purchases	1	1	5	2	0	9	1,04
	P3) Reduce bias from historical data patterns	1	0	5	1	0	7	0,43
Source	P4) Enabling reliable mid-term demand planning by informing the supplier on a timely manner for the quantities expected	2	2	7	3	2	16	0,94
	P5) Ensuring reaction to possible variation on short notice - Planning reactive capacity	2	0	4	2	0	8	0,47
	P6) Benchmarking promotional activities and new product introduction	2	2	3	0	0	7	0,83
Make	P7) Evaluate and predetermine the valorization point for products that produce a lot of sub-products	0	0	0	2	2	4	1,01
Deliver	P8) Making available/interpretable granulated demand and similar data for ordering decision support	2	1	6	4	0	13	1,16
	P9) Determine the distribution plan for pooled bulk purchases	0	0	6	4	2	12	1,18
	P10) Ensure inbound compliance enforcement	0	0	5	5	1	11	0,5
	P11) Ensure efficient in-store personnel deployment & space shelf planning	0	1	3	0	0	4	1,19
Return	P12) Reduce reverse flows because of unnecessary buffer inventory	0	0	5	0	0	5	1,16

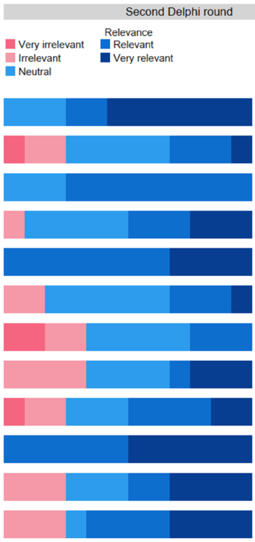

Fig. 2 Left: expectations from an advanced forecasting tool based on BDA; Right: proposition ranking for planning advancement expectations from increased forecasting accuracy

	First Delphi round						Second Delphi round
Potential Demand Sensing Features	Category Management n=2	In-Store Audit n=2	Operations Management & IT Infrastructure n=8	Procurement & Distribution n=6	Product Quality Assurance n=2	Total (n=20)	Votes
Advanced weather data	2	2	8	6	2	20	15%
Best before date							13%
Assortment width	2	0	4	2	0	8	11%
Consumer location mobile data	0	0	2	2	0	4	10%
Promotions	2	2	6	6	2	18	10%
Consideration of goods sold on discount and the reasons for the discount							8%
Holidays - And potential shift through the year	1	0	4	4	0	9	7%
Salary income day	1	1	7	4	0	13	7%
Density of supply in area							3%
Packaging size and material							3%
Social and political components i.e., strikes	0	0	0	0	2	2	3%
Specific recursive events i.e., concerts, tournaments	2	2	8	6	2	20	3%
In-store facing inventory level	2	2	5	3	0	12	2%
Logistics bottlenecks	0	0	0	2	0	2	2%
Substitutionality (Intermittence)	1	2	4	4	0	11	2%
Vacation periods	3	1	5	3	1	13	2%
Availability of in-store employees for customer service rather than operations	0	0	3	2	0	5	0%
Proper categorization of fast movers	1	0	2	0	0	3	0%
Shopping cart	0	0	3	2	0	5	0%
Social media trends	2	0	4	2	0	8	0%

Fig. 3 Left: influences and factors as predicting features (blank rows represent features that were added during the discussion in the second Delphi round); Right: prioritization of demand sensing features

measures of interest parallelized with food waste prevention. The frequencies of the first Delphi round represent the number of statements by each respondent group. The latter were categorized based on the function in the corresponding enterprise. From the quotations during the semi-structured interviews, 26 propositions related to expected supply chain planning implications, horizontal collaboration levers, and performance measures related to food waste prevention were deductively derived based on content analysis. Furthermore, 17 potential demand-sensing features were extracted. During the first topic discussions, essential to notice is that all respondents are agreeing unified that the forecasted data is to be shared in the supply chain and that the full potential of available external and internal data is unharvested.

The second round was conducted in a focus group workshop format with 12 experts from the affiliated companies. The goal was to rank by consensus the derived propositions and ultimately guide the development of a FSS. Initially, the results of the proposition deduction from the first Delphi round were presented. Further on, the results from each proposition group were readdressed as specific discussions. The respondents ranked each proposition on a Likert scale from 1 to 5 (respectively,

First Delphi round						
Coopetition Driven Propositions	Category Management n=2	In-Store Audit n=2	Operations Management & IT Infrastructure n=8	Procurement & Distribution n=6	Product Quality Assurance n=2	Total (n=20)
Determining minimum optimal order quantities	0	0	5	2	0	7
Competitors historical data on promotions	2	0	6	2	0	10
External feature data validation	0	0	6	0	0	6
Sharing best practices in logistics	0	0	0	3	0	3
Managing reusable packaging	0	0	0	3	0	3
Purchasing Communities esp. fresh and ultra-fresh imports	2	0	4	1	0	7

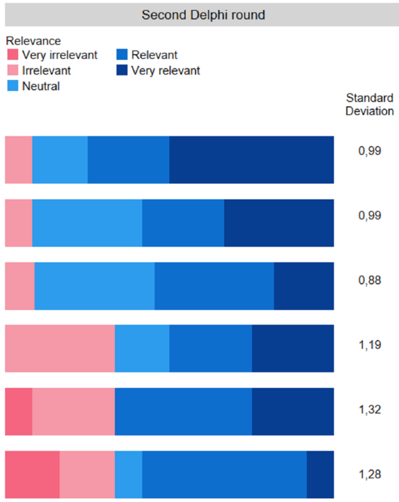

Fig. 4 Left: Potential horizontal collaboration levers; Right: Proposition ranking of horizontal collaboration levers

First Delphi round						
Performance measures parallelized with food waste prevention	Category Management n=2	In-Store Audit n=2	Operations Management & IT Infrastructure n=8	Procurement & Distribution n=6	Product Quality Assurance n=2	Total (n=20)
Out of stock	2	2	7	5	2	18
DSS recommendation acceptation quote as an automatization	0	0	4	3	0	7
Product quality offered to end consumers	1	2	4	3	2	12
Turnover for inventory held	0	0	2	3	0	5
Environmental sustainability	0	0	4	0	2	6
Warehouse workflow day-to-day variance	0	0	4	5	0	9
Fair pricing from farm to fork	0	0	4	0	2	6
Staffing costs	0	0	3	3	0	6

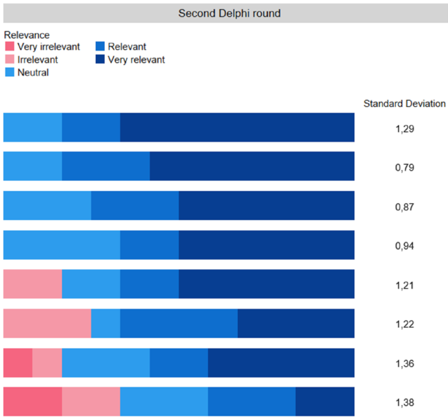

Fig. 5 Left: Performance measures parallelized with food waste prevention; Right: Proposition ranking for performance measures that parallelize with food waste mitigation

from non- to extreme-relevancy), corresponding to the discussion groupings. Based on current practices, as reviewed by Giannarou and Zervas (2014), the consensus is measured by the "very relevant" percentage of responses in the Likert scale and standard deviation. Furthermore, propositions that follow bi-modal distributions are considered non-consensual (Powell 2003). The demand-sensing features derived from question 2 are ranked based on voting to increase interaction during the focus group workshop and are shown in Fig. 3. Such ranking is crucial because it facilitates the development of the forecasting tool. By prioritizing certain features based on their importance, the tool can be designed to meet the stakeholders' needs effectively. Furthermore, prioritization eases technical development efforts for data integration.

The left side of Fig. 2 depicts a forecasting tool's expected planning advancements toward food waste prevention. The focus remains on internal practices and supplier-dependent operations based on the SCOR framework. As Akkas et al. (2018) point out, the empirically collected propositions in the planning sphere indicate that supply chain age is a driver of food waste at the shop-floor level. In that regard, almost unanimously, it was stated that an advanced forecasting tool's main serve is synchronizing supplier operations to ensure product quality in terms of shelf-life by reducing the supply chain age. Further on, attention was brought to the development of reactive capacity because of supply uncertainties (Cachon and Terwiesch 2013). In this regard, a respondent from the procurement function in company I stated, "Because of supply chain uncertainties, specific fresh imports such as fish are ordered at 3–4 suppliers to consolidate the expected demand. Therefore, there is either more than needed or an out-of-stock situation". In this case, the role of the forecasting tool would be to include supplier reliability. Especially for small-scale suppliers, sharing demand realization expectations enables routing coordination as a lever for food waste prevention (Soysal et al. 2015).

Bias reduction from historical patterns was stated as an essential point. As stated by one of the respondents in the IT infrastructure from company I, "When it comes to food waste reduction, it is more valuable if the decision support system tells that even though there was a crest during a specific week in the last five years, this pattern should be ignored because the situation might have changed." This statement indicates that complete reliance on historical data might not necessarily produce the best results from an overstocking perspective. In a novel manner, the role of the decision support interface weighted the discussions. One of the respondents in the operations management function in company II stated, "Looking for example at the write-offs from expired yogurt with a shelf life of 14 days and the opportunity to order daily, much waste is human factor-driven". Such a setting indicates that the ordering process is overruled by employee experience as a judgmental factor. In this context, company III introduced a performance measure called the DSS recommendation acceptance quote. Such performance measure indicates the level of automation in the replenishment process as a lever for potential forecast improvement. Based on these extractions, it can be inferred that the supply–demand matching paradigm, which consequently results in food waste, is partially driven by exception management practices. While considering the trade-off between data-driven versus human reliance (Kache and Seuring 2017) for such replenishment processes, automation has a twofold role, (i) It ensures proper coverage of current expectation management practices, and (ii) makes in-store employees available for customer service rather than operations. The latter is stated as a potential demand-sensing feature during the first-round interviews.

On the right hand-side of Fig. 2, results from the proposition ranking derived from question 1, namely, the expectations from an advanced forecasting tool to enable planning with food waste prevention considerations, are shown. Primarily, the forecasting tool is expected to encompass supply synchronization with perishable producers to reduce the supply chain age and consequently increase the quality of the products in the store. Such a setting leaves to understand that forecasting attempts are expected to be forged in supply operations. Elaborating on the reliance paradigm by Kache and Seuring (2017), such a data-driven tool is seen as a facilitator of ordering decisions being supervised by employees. As product orders are often influenced by employees based on unquantifiable externalities, an advanced forecasting tool is expected to facilitate such processes through accessible information.

Furthermore, a forecasting tool is expected to enable reactive capacities during supplier disruptions or economization efforts. Reactive capacities pave the way to address supplier diversity from a service cost and food waste mitigation perspective.

Bias reduction from historical data patterns is considered an expectation from the advanced forecasting tool compared to currently deployed methods. 75% of respondents evaluated the proposition as relevant.

After the individual conduction of the Likert questionnaire, the results were presented to the focus-group expert panel. It was bodily decided that the development of the advanced forecasting tool should first-hand (I) serve as a supplier synchronization framework, (II) facilitate exception management in product ordering, (III) enable reactive capacity, and (IV) handle historical patterns bias.

The extracted potential demand sensing features are ranked on the right side of Fig. 3. The left side again shows the number of mentions derived from the first Delphi round. Importantly to note is that during the discussions, some of the proposed features got merged, and new ones were additionally introduced. These can be seen by the blank rows on the left side of the figure. The empirically extracted features represent the fundament for further project development, i.e., the forecasting framework for food waste prevention.

Weather patterns and recursive events are the most stated features for enriching forecasting methods. Regarding weather patterns, one of the respondents from the procurement and distribution function in company III stated, "Weather is a continuous predictor. Some products are sold in good weather, some in bad weather". This view is supported for example by the work of Rose and Dolega (2022), who found that impact of the weather is especially strong in the summer and spring months with health foods being the most susceptible product types. Interestingly, the salary income day was often stated by the respondents from the corresponding three companies. Specific recursive events also received the highest number of mentions by the experts, meaning the influence of large accumulations of people for example during concerts and tournaments, which are not easily foreseen by data-driven systems. Such events occur sporadically and are likely to be known by the system user, who needs to be able to adjust the forecast values accordingly. Nevertheless, the possibly resulting double accounting effect, which results from consideration in both the forecast and the adjustments needs to be considered (Khosrowabadi et al. 2022).

The best-before date per product is voted the second most important feature due to its direct supply planning implications. The latter is argued as a constraint to the minimum forecasting accuracy expected to prevent food waste. Additionally, the best-before date of the current inventory level is considered as an indirect influencer of consumer preferences. Furthermore, integrating best-before information enables age-based replenishment policies that tend towards food waste reduction (Haijema and Minner 2019).

The assortment width per product is voted the third most important demand sensing feature. The significant influence of the assortment width is also concluded in Riesenegger and Hübner (2022) and Gruber et al. (2016).

Consumer location mobile data as a means to make events measurable was mentioned four times during the first Delphi round but received the fourth-highest rank among the demand sensing features. This measure can make unusual accumulations of people visible and quantifiable by comparing the number of permanent residents in a specific area to the number of additional visitors. Especially in the analysis and planning of retail stores, the use of anonymized mobile phone network data has emerged as a research field (Cik et al. 2020; Lechner 2018; Stadlbauer 2019; Waßmuth 2018).

Promotions received the third place when it comes to the number of mentions and share the fourth rank together with the previous feature. Abolghasemi et al. (2020a) prove, that the inclusion of promotional data within the forecast in order to minimize human judgement needs is beneficial. This also helps to overcome the tendency of people to over-adjust and therefore harm model accuracy (Sroginis et al. 2023).

To sum up the findings summarized in Fig. 3, demand sensing feature prioritization is essential due to the influence on the forecasting tool's technical development efforts. Certain features that were ranked with 0% were discussed during the first round of interviews but were not ultimately voted on. In that case, the experts considered the resources required to develop and implement these features would be better spent on the highly voted ones.

Further on, Fig. 4 represents the coopetition-driven propositions. This group summarizes propositions for horizontal collaboration as a lever to facilitate food waste prevention activities. Remarkably, this part of the questionnaire faced much hesitance because of the measures enforced by the competition authorities in the country where the responding firms operate. However, the affiliated companies are active members of the ECR initiative in Europe (ECR 2023). Competition historical promotions were stated as important information that can facilitate better forecasts in the future. However, such information acquirement is lawfully limited to publicly available sources. In this regard, the "mailbox" information source was mentioned as an alternative. The mailbox information source represents historical leaflets that directly reach end consumers, gastronomies, event management, etc. This setting would further enlighten the trade-off between information absorption capacity and appropriability while considering potential data leakage (Ritala and Hurmelinna-Laukkanen 2013).

Also, validating external features was seen as a lever for collaboration from a knowledge-sharing perspective. From a logistics operation point of view, the development of purchasing communities to optimize costs and reduce emissions was stated as an already-initiated model. Further on, willingness to share best exception management practices was mentioned as a novel lever. As stated by one of the respondents in the procurement & distribution function in company III, "We are all cooking in the same water, we can only support each other with best practices".

The right side on Fig. 4 presents the ranked propositions based on corresponding consensus measures. The minimum order quantity per product was considered a possible lever induced by horizontal collaboration. Determining such is part of the ECR initiative in which all the consortium partners are active members. Sharing historical data on promotions caused uncertainty during discussions, as it is prohibited by local law authorities. Furthermore, logistics and purchasing practices are considered individual competencies among experts. This causes hesitancy to formalize the interchange of best practices and consequently develop purchasing communities. Uncertainty also arose in managing reusable packaging due to its role as an indirect information source. The possibility to infer process performance and indirect information obtainable from validating external data cast hesitancy among the respondents. Ultimately it consented those methods for sharing information as a lever for horizontal collaboration are adaptable for specific circumstances. The focus group workshops in the context of the consortium towards food waste prevention served as a knowledge and best practice sharing platform.

Last but not least, Fig. 5 represents the collected statements for additional performance measures that parallelize to food waste prevention. The right hand-side of Fig. 5 represents the ranked propositions from the second Delphi round. Out-of-stock was an almost unanimously mentioned performance measure, stating the frequency or duration of products being unavailable for sale or out of inventory (Levy and Grewal 2023). It is the most prevalent performance measure based on the relevancy percentual share of respondents in the Likert scale.

The second most important performance measure of interest is automating the replenishment process, i.e., accepting the recommended quantity. The automation quota for the replenishment process is argued as important as it (i) reduces last-minute interventions, i.e., afore sales, which are prevailing (van den Broeke et al. 2019) (ii), and serves as a performance measure for the forecasting tool especially when external features are integrated. The focus group debate remained open in the balance between pure data-driven reliance and the human factor in the perishable product replenishment process. This debate paves the way to research the allowed intervention points throughout the product flow. This discussion streamlines with the role of human judgement, that plays a crucial role when it comes to the acceptance of a FSS in practice (Fildes and Goodwin 2007). Automated systems can provide valuable insights and can help to improve efficiency (Kiil et al. 2018), but incorporating human expertise and judgment into the replenishment process ensures that decisions are based on a range of factors and account for unquantifiable externalities. The decision support interface appropriation is an achievement burden to this balance (Sroginis et al. 2023).

This is followed by the product quality offered to end consumers, i.e., the level of excellence or satisfaction achieved by a product in meeting the expectations and needs of the end consumers (Besterfield et al. 1995). Due to the supply planning expectations (see: proposition ranking from Fig. 2), 50% of the respondents considered product quality offered to end-consumers a prominent performance measure.

Turnover from inventory held as a basic and known performance measure in the domain of logistics and supply chain management (Stevenson et al. 2014) is ranked as the fourth most-important performance measure in the context of food waste prevention.

Environmental sustainability was ranked fifth place among the features, as defined by the environmental impact associated with food retail, including the food waste rate and Greenhouse Gas Emissions (see e.g., FAO (2023), Marsden and Morley (2014) for relevance). In the focus group workshop, environmental sustainability is discussed as a critical concern due to its implications in the replenishment process. The relation between minimum order quantity, transportation frequency, and food waste are focal to the environmental impact discussion. The balance between such attributes is foreseen as a solution. In the context of food production, this can involve producing smaller lots of food more frequently rather than producing large quantities all at once. However, it is essential to consider that reducing lot size and increasing order frequency can also have an impact on the overall environmental sustainability of the production and distribution system.

There was no consensus among the focus group regarding the rest of the performance measures. Some members strongly favored certain propositions, while others disagreed or opposed them outright.

4.2 Implications and consequences of the findings for the development of a data-driven FSS

This research aims to identify structural and functional elements which an advanced FSS based on heterogeneous big data is expected to contain. For a more detailed elaboration of those elements and the overall IT architecture, the reader is referred to Birkmaier et al. (2023). An overview of the architecture is depicted in Fig. 6.

Structure-wise, the implications of the Delphi study show some additional points in contrast to the existing literature and some general requirements for the overall system architecture. First, the data layer containing an Extract, Transform, Load (ETL) process is needed, which is capable of extracting from a direct interface to the company's Enterprise Resource Planning (ERP) system, transforming, and loading the heterogeneous data into a form, which is suitable for the algorithms in use. The process includes the company-internal data, i.e., transactional data, and external mobile transaction data and weather data. The continuity of such a process is considered one of the main challenges in deploying advancements in planning methodologies (Khosrowabadi et al. 2022). The second architectural layer is the logic layer, in which the selection of the optimal replenishment policy takes place based on the forecast sales quantities. Another implication of the Delphi study is that the interaction layer of the system requires intervention possibilities for the user. More extensive and contextual knowledge of the user demands a possibility of adjusting the ordering plan as a final output. The data visualization layer of the FSS needs to fulfill two functions based on the results. First, it must provide the user adequate information on what factors were considered during the forecasting process. Second, the system shows the food waste-related performance measures, including expected waste, the confidence interval of the result, and the identified parallelized performance measures.

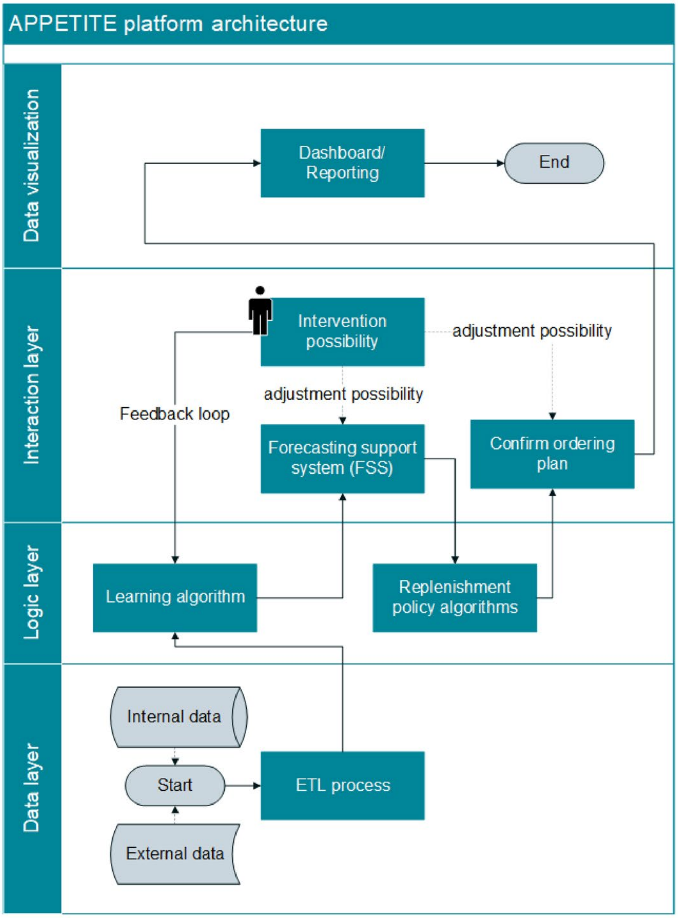

Fig. 6 Conceptualized APPETITE platform architecture based on Birkmaier et al. (2023)

To address the requirements of the FSS, several AI-based and classical statistical methods are suitable. Existing literature in the context of perishable food forecasting has shown the effectiveness of Support Vector Machines in combination with Boolean promotional data (Di Pillo et al. 2016). Also, Long Short-Term Memory Networks (LSTM) have been successfully combined with multiple weather-related attributes (Liu and Ichise 2017). LSTM, Random Forests, and Bayesian Hierarchical Modeling are combined with holiday seasons by Tiainen (2021). The implications of the work suggest using hybrid forecasting methods to assure the needed trustworthiness and effectiveness of the FSS. Hybrid methods use a combination of multiple machine learning (ML) methods and benefit forecast quality by outperforming more straightforward AI-based methods (Li et al. 2018; Pavlyshenko 2019). The advantage of combining multiple methods or models is that the single methods are better understood and can be explained. Allowing better reasoning about the complex hybrid model can lead to a better understanding of ML models in general.

5 Discussion

Reducing supply chain age, i.e., increasing in-store quality, by facilitating the synchronization of replenishment levers with the perishable food producer is foreseen as the primary expectation from the forecasting tool. Product supply chain aging drives the inventory calls from upstream based on transportation batching and safety stock (Akkas et al. 2018). A further expectation pointed out is facilitating product ordering by integrating unquantifiable externalities in the decision support interface and enabling reactive capacity ordering. Judgmental adjustment-based methods account for around 40% of surveyed deployments (Sroginis et al. 2023). Determining the last judgmental intervention point during the product flow in the supply chain is a topic of interest, especially from a food waste prevention perspective.

Furthermore, the system is expected to determine possibilities for reactive ordering to cope with demand uncertainties (Fisher et al. 1997). This is argued based on the better freshness-keeping efforts at the perishable supplier than the retailer due to in-between transportation. Transportation of perishables indicates a complex interactive system that impacts temperature maintenance and, consequently, deterioration rate (James et al. 2006). Furthermore, facilitating reactive capacity planning can serve as a supplier diversification base where a form can be based on enabling order consolidation from diverse small-scale suppliers (Fikar and Leithner 2021; Soysal et al. 2015).

Human behavior constitutes another relevant factor, as the perceived trustworthiness of the forecasting system is a determinant for the acceptance and use of the forecast (Khosrowabadi et al. 2022; Lehmann et al. 2022). Khosrowabadi et al. (2022) found that price, freshness, and discounts are factors considered by supply chain planners when making adjustments to the forecast. In general, planners do not contribute to the accuracy of forecasts, making frequent but inaccurate significant positive adjustments and less frequent but more accurate negative adjustments to system-based forecasts. In this context, the results of the Delphi study reveal a need for explainability of the system results, i.e., which factors led to the forecast quantity. Explainability is essential as no double influence occurs in the readjustment of order quantities, and trust in the system can be grown. In this regard, research suggests Human-Guided Learning as a method to integrate human judgment for demand planning, which can be more accurate under certain circumstances (Brau et al. 2023). In our research, this is indicated by the need to re-feed the adjusted ordering plan into the system to improve the forecasting process.

Bias reduction from historical data patterns was foreseen as an expectation due to supply chain disruptions caused by unprecedented situations. Time series data are considered heavily influenced by these disruptions. In that regard, quantitatively integrating factors that influence a specific demand pattern is foreseen as necessary, consequently reflecting an expectation for the forecasting tool development.

Judgmental factor identification for demand sensing in grocery retail is promotion-based and is extensively researched in the marketing literature. In our study, important criteria proposed for factor prioritization were quantifiability and adaptability. Furthermore, voted factors prioritizing the integration efforts are not considered independent, especially during a promotion schedule.

Even though the corresponding companies are part of a consortium towards food waste prevention, horizontal collaboration faced hesitance as a topic due to cartel acts and competition law. The effort to consolidate the assessment of minimum order quantity towards food waste prevention was confirmed. The latter is part of the ECR initiative. The rest of the propositions faced discrepancies and are expected to be treated after lawful consideration. Investigating horizontal collaboration practicality is not aligned with competition law and its implications for unfair trade practices in Europe (Directive—EU 2019). Allowance for specific horizontal collaboration practices beyond the competition law is proposed to be argued based on food waste reduction, which consequents an added value for the end consumer. Such practices point out further research opportunities. Product availability is a significant concern in grocery supply chain operations (Aastrup and Kotzab 2010). The tendency to balance supply and demand through advanced planning is expected to avoid aggravating the out-of-stock problem. Furthermore, judgmental interventions on recommended quantities on the shop-floor, i.e., right before sales, are foreseen to get mitigated. The balance between pure data reliance and the human factor in replenishment planning is expected to be supported with relevant interface-based information.

6 Conclusion

This explorative research maps the industry expert expectations and prioritizes demand sensing features for developing a forecasting tool for food waste prevention. Furthermore, it elaborates on the role of horizontal collaboration, i.e., coopetition, and identifies performance measures parallelized to food waste prevention interventions. The derived implications are a prioritization base for developing a comprehensive forecasting tool and other add-on concepts for wasteless supply chain planning. Moreover, the identified propositions enable better decision-making within companies and serve as incentives to improve operational performance. This research has shown that companies are well aware of the fact that sharing information horizontally and vertically is beneficial to their business. Still, they are reluctant to share it directly, indicating space for information leakage. Prescriptively, if information and knowledge are shared in (near) real-time, i.e., historical promotion plans, current food waste drivers, and product quality expectations, additional value could be created through potential food waste prevention by a holistic and data-driven planning approach.

The explorative study additionally maps judgmental factors for demand forecasting. The results may differ from other food supply chain configurations or the entire industry. The integration of the ranked demand factors requires additional research as they are not treated independently from each other. The identified propositions indicate future research paths. This research can link the empirical propositions identified to confirm existing solutions for food waste prevention in the current body of knowledge.

Furthermore, conceptual work on defining frameworks for reducing food waste would be the next research step. The supplier coordination-demand forecasting reciprocal impact is interesting to investigate. Of interest is also the investigation of the paradigm between pure data reliance and human judgment in ordering decisions and the impact of the appropriate intervention point, i.e., judgment factor integration, throughout the product flow in the supply chain. Ultimately, the integration of the derived insights in the development of a decision support tool to improve the accuracy and efficiency of forecasting tools for food waste prevention is the ultimate future outcome.

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Data availability The data used as a base for this paper is available and stores safely. It can be made available upon request. The datasets generated during and/or analysed during the current study are not publicly available due to individual privacy of the interviewees but are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Informed consent A letter of consent was provided to the interviewees prior to the interviews and explained. Each interviewee signed the letter of consent prior to conducting the interview.

Research involving human participants and/or animals This research included interviews conducted with human participants. The interviewees were prior informed in a written form about the procedure and questions answered in the interviews and signed a letter of understanding. All results were later shared with the participants.

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