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Grocery omnichannel perishable inventories: performance measures and influencing factors

Abstract

Purpose: Perishable inventory management for the grocery sector has become more challenging with extended omnichannel activities and emerging consumer expectations. This paper aims to identify and formalize key performance measures of omnichannel perishable inventory management (OCPI) and explore the influence of operational and market-related factors on these measures.

Design/methodology/approach: The inductive approach of this research synthesizes three performance measures (product waste, lost sales, and freshness), and four influencing factors (channel effect, demand variability, product perishability, and shelf life visibility) for OCPI, through industry investigation, expert interviews, and a systematic literature review. Treating OCPI as a complex adaptive system and considering its transaction costs, this paper formalizes the OCPI performance measures and their influencing factors in two statements and four propositions, which are then tested through numerical analysis with simulation.

Findings: Product waste, lost sales, and freshness are identified as distinctive OCPI performance measures, which are influenced by product perishability, shelf life visibility, demand variability, and channel effects. The OCPI sensitivity to those influencing factors is diverse, whereas those factors are found to moderate each other's effects.

Originality/Value: This paper provides a novel theoretical view on perishables in omnichannel systems. It specifies the OCPI performance, beyond typical inventory policies for cost minimization, while discussing its sensitivity to operations and market factors.

Practical implications: To manage perishables more effectively, with less waste and lost sales for the business and fresher products for the consumer, omnichannel firms need to consider store and online channel requirements and strive to reduce demand variability, extend product shelf life, and facilitate item-level shelf life visibility. While flexible logistics capacity and dynamic pricing can mitigate demand variability, the product shelf life extension needs modifications in product design, production, or storage conditions. OCPI executives can also increase the product shelf life visibility through advanced stock monitoring/tracking technologies (e.g. smart tags or more comprehensive barcodes), particularly for the online channel which demands fresher products.

Keywords: omnichannel, grocery, consumer order fulfillment, perishable inventory, shelf life, data visibility.

1. Introduction, research objectives, and contributions

Moving beyond offering multiple online and offline sales and delivery channels, contemporary retail strives to provide a uniform and seamless experience to consumers throughout the shopping and consumption journey; this is widely known as omnichannel (Lim and Srai, 2018). Omnichannel is a growing trend in grocery retail, whose role in perishable products like fresh food is crucial to the competitiveness of retailers. This research views the omnichannel perishable inventory (coined as "OCPI"), as a complex system (as explained below), influenced by various factors. Accordingly, this paper aims to: (*i*) define the key performance measures for the OCPI system, which incorporate its product perishability implications for consumer and for operations, (*ii*) identify critical factors influencing OCPI performance measures, and (*iii*) investigate the sensitivity of performance measures to the changes in these influencing factors. To address the inherent complexities in OCPI systems as well as their multiple operations and market perspectives, this research explores OCPI through the theoretical lenses of the complex adaptive system theory (Nilsson and Darley, 2006) and transaction costs theory (Luzzini *et al.*, 2012). Complex adaptive systems can change their configuration to influence their current and future survival; they have multiple agents interacting with and depending on each other (Nilsson and Darley, 2006). The complex adaptive system theory helps our analysis of OCPI complexities and exploration of the required adaptabilities to manage its performance. Transaction cost theory assists this research in understanding and explaining the market choices of channels and the operations decisions required to respond to them.

The contribution of this paper is threefold: (*i*) product waste, lost sales, and freshness with their features, specific to perishables and the omnichannel environment, are recognized as key OCPI performance measures; and four factors, namely, "channel effect", "demand variability", "product perishability", and "shelf life visibility" are identified as influencing OCPI decisions and performance; (*ii*) the collective effects of those factors on OCPI performance are found mixed and diverse, and; (*iii*) sensitivity of OCPI systems to the influencing factors is examined and explained.

To the best of our knowledge, the perishable inventory management literature has not yet expanded to the omnichannel context, and the omnichannel literature is still progressing to consider the features of perishables and their influencing factors in order to manage the inventories across multiple channels (for details, see the literature review in Section 2). Perishable inventory models need to incorporate the specific challenges of omnichannel systems, such as stock availability, stock sharing, enhanced levels of data accuracy, and channel-specific expectations of product age, freshness, quality, and delivery; but the answers to those requirements/challenges do not exist in the current omnichannel inventory policies and models.

This paper is organized as follows. The literature underpinning the research is shared in Section 2. The research design and methods are explained in Section 3. Grounded on the complex adaptive system and transaction cost theories, this research integrates the OCPI features, industry practices, and expert opinions through a systematic literature review (SLR), industry investigation, and interviews to develop its statements and propositions, as elaborated in Section 4. The research's propositions are then examined through a numerical analysis (using simulation and design of experiments), and the results are discussed in Section 5. Finally, concluding remarks and further discussions on the theoretical and managerial implications of the research outcomes are shared in Section 6.

2. Underpinning literature

Omnichannel frameworks typically include combining conventional and e-commerce retail models such as click & collect, buy-online-pickup-in-store, reserve-online-pickup-in-store, buy-in-store-ship-home, and buy-online-ship-home (Lim and Srai, 2018; Bayram and Cesaret, 2020; Vyt *et al.*, 2022; Yang and Zhang, 2020). The omnichannel literature includes inventory control in multiple channels (Barratt *et al.*, 2018), customer order fulfillment (MacCarthy *et al.*, 2019), last-mile delivery (Hübner *et al.*, 2016), ship-to-store/ship-from-store models (Arslan *et al.*, 2020), and product returns (Frei *et al.*, 2020). Emerging omnichannel literature also includes inventory assortment planning over multiple channels (Melacini *et al.*, 2018), information systems integrations required for the omnichannel (Saghiri and Mirzabeiki, 2021), bullwhip effect in multi-channel supply chains (Ma *et al.*, 2019), and multi-channel pricing strategies and profitability (Ishfaq and Bajwa, 2019). Du *et al.* (2019) find that the store's inventory could support online consumers; – i.e. in case online consumers do not receive their orders through a home delivery system, they can visit the store. Hajdas *et al.* (2020) and Lan *et al.* (2018) encourage inventory sharing and collaboration among channels to manage demand volatilities. They also emphasize the obstacles toward inter-channel inventory integration, but with no further detailed analysis.

Overall, despite its growing popularity, the omnichannel literature is scarce in regard to perishable products and inventories which have special characteristics with peculiar requirements and implications (as addressed below) for omnichannel systems (Hübner *et al.*, 2019).

Perishable inventory management theories date back to the 1970s (Pierskalla and Roach, 1972) and a number of review articles and textbooks have summarized the latest progress in this field (Bakker *et al.*, 2012). However, the research on perishables in the omnichannel environment (and its special conditions) is underdeveloped. Perishables such as fresh foods and beverages require storage temperatures of around 4-10^{o}C, throughout their journey toward sales and delivery (in warehouses, stores, and delivery vehicles). They also have smaller batch sizes compared to non-fresh items, more frequent deliveries than slow-moving products, and short replenishment lead-times (Eriksson *et al.*, 2019), with substantial implications for stock keeping-points and store density (Belavina, 2021), as well as product flow management and logistics in the omnichannel (Melacini *et al.*, 2018) – i.e. where to locate the stores, where to keep the stocks, and in what sequence to plan the deliveries. These unique features make a study on grocery perishable inventories in the omnichannel context significant and interesting, as elaborated further below.

Advances in information and communication technologies as well as the recent extensive disruption by Covid-19 have created a major shift toward online grocery shopping (Sarkis, 2021). Additionally, operational costs and labor-/time-consuming tasks within supermarkets, associated with frequent replenishment, shelving, and disposal of perishable items, drive retailers to expand their online grocery sales (Reiner *et al.*, 2013).

Nevertheless, the expansion of online channels depends on many factors including the market potential, product features, and logistics requirements. Regarding the market, fresh foods and other perishables are of particular importance in the grocery sector. Food and grocery sales have had an annual growth of 4% in the UK in recent years, and are expected to reach £220bn by 2023 (Carroll, 2019; Crisp, 2018). Foods contribute to the majority of grocery stores' revenue (Herbon, 2017): for every pound spent in UK retail, 39 pence is spent in food shops, contributing to 2% of the total economy output (Rhodes, 2018).

Notwithstanding their substantial share of the grocery market, perishables have inherent characteristics and logistics requirements, which prevent the whole grocery business from simply turning to online channels. Business reports reveal that while 48% of consumers may engage with online channels, only 8% of them do their grocery shopping solely online (Carroll, 2018), and around two-thirds of consumers have experienced some issues with their online grocery orders (Carroll, 2019). Kumar *et al.* (2017) also show that although 80% of executives in the consumer-packaged-goods industry have been trying to move the grocery business toward online and omnichannel platforms, due to the complexities of grocery retail only 25% of them are optimistic about its results. Hübner *et al.* (2019) and Weber and Badenhorst-Weiss (2018) specify the distinctive challenges for omnichannel retails of perishables, such as temperature-controlled (at multiple levels) distribution, product short shelf life, product non-returnability, consumer expectation for quick delivery, and retailers' complex order fulfilment processes. Their focus is mainly on the last-mile delivery and logistics of the perishables.

The perishables' online sales and the required logistics around it (e.g. product home delivery) are affected by various consumer shopping behaviors (e.g. expectations of product freshness and delivery time-slot) and the need for consumer attendance to receive the product (Pan *et al.*, 2017). Furthermore, consumers usually need their orders of perishables to be delivered quickly, even immediately (e.g. in case of buying a lunch sandwich or baby food). Perishables might not always have a uniform shape or content (e.g. no two chicken salads or raspberry packs are exactly the same), so some consumers may prefer to see the product before buying it (i.e. less motivation for online shopping). Relatedly, since consumers do not see the perishable product's quality as stable during its lifetime (i.e. product deterioration rate may vary in different conditions), the demand for it is not stable either and is broadly motivated by product freshness and shelf life; hence the perishables' sales are typically time-, stock-, and/or price-dependent (Bakker *et al.*, 2012; Haijema and Minner, 2019).

Offering perishables in an omnichannel system also needs up-to-date inventory data in various channels. This needs more frequent inventory checks and continuous inventory review models

(Hill, 2007; Schneider and Klabjan, 2013). Along the same line, Bakker *et al.* (2012) and Janssen *et al.* (2016) underline the need for more product data visibility, such as expiry date, for perishable inventories. Siawsolut and Gaukler (2019) and Siawsolut and Gaukler (2021) study perishables in the omnichannel context and show that advance orders from the consumer lead to reduced replenishment lead time, lower rate of product deterioration, and higher level of product availability. He *et al.* (2019) argue that online channels reduce product waste.

In sum, our review indicates that although inventory planning is found vital in retail management (Mou *et al.*, 2018; Song *et al.*, 2021), we are yet to learn about the implications of operating in the omnichannel environment for special inventories like perishables, while specific issues around consumers' shopping behavior and retailers' stock ordering, replenishment, fulfillment, and delivery decisions for perishables demand further attention. In view of that, this research fills the literature gaps by recognizing product waste, lost sales, and freshness as the crucial performance criteria of perishable inventories in the omnichannel system, and identifying their sensitivity to key influencing factors of "channel", "demand variability", "product perishability", and "shelf life visibility".

3. Methods

This paper adopts an inductive approach to develop its statements and propositions, and analyze them numerically (Boer *et al.*, 2015). This is very much compatible with Handfield and Melnyk's (1998) recommended research road map, which has been widely used to build and elaborate operations management theories over the last two decades. Thereby, qualitative research (based on expert interviews, industry documentation, and literature) coupled with numerical analysis provides a strong foundation for this paper. The study is designed based on the following steps: (*i*) SLR to explore the perishable inventory management research in the omnichannel context and extract OCPI performance measures and influencing factors; (*ii*) industry investigation and expert interviews to triangulate the SLR findings and formulate the effect of influencing factors on OCPI performance in the form of two statements and four propositions; and (*iii*) numerical analysis (including simulation and statistical tests) of OCPI performance sensitivity to the influencing factors. These steps are summarized in Figure 1 and explained in the following Subsections.

Figure 1. here

3.1. Systematic Literature Review (SLR)

SLR, conducted to explore OCPI performance and influencing factors, is widely known as a structured referential method to review and synthesize the existing body of knowledge with a rigorous process (Seuring *et al.*, 2021). Although the SLR was originally defined for well-established bodies of knowledge, it has been increasingly employed in new and emerging research areas in recent years (Brax *et al.*, 2021). Thus, the SLR in this paper tracks the following steps (Seuring *et al.*, 2021): research question definition, primary study, relevant literature sample selection, literature synthesis, and report preparation.

Three major databases – ABI, SCOPUS, and EBSCO – have been searched using search strings that are defined in the domains of perishable products and inventory. Initially, 1019 articles have been refined and distilled in multiple rounds, and finally, 155 relevant papers have been studied in detail. Several key areas, including the objectives (performance measures) of perishable inventory systems, types of demand for perishables, and various types of product shelf-lives, have been identified - full details of the SLR outcomes are available as an online supplement to this paper. The results are organized in a number of key performance measures and influencing factors on OCPI and form a basis for the next steps of this research, where they are further investigated in business practices, and discussed in expert interviews.

3.2. Industry investigation

This part focuses on reviewing the grocery retail multi-channel and omnichannel policies and practices. Six UK groceries (ASDA, Harrods Food, Morrisons, Sainsbury's, Tesco, and Waitrose), which represent various levels of progress toward omnichannel (i.e. offering integrated store and online sales and delivery options), are studied. Secondary sources of data, including the companies' websites, their policies and reports, and white papers and articles about the companies' omnichannel practices, are considered (100+ e-documents/documents are studied in total). This helps the study investigate and understand the recent actions by the retail industry leaders in terms of online sales, order fulfillment procedures, consumer perception of perishable products' freshness and availability, waste management policies, and product delivery practices.

A complete understanding of the companies' omnichannel processes and practices has been made possible through this industry investigation. Relevant power-quotes/citations from the companies' data are provided to support the research statements and propositions (Table I).

3.3. Expert interviews

The SLR's and industry investigation's outcomes are further discussed in semi-structured expert interviews, which help the inductive phase of this research to achieve an in-depth understanding of the OCPI complex phenomenon and associated 'why' and 'how' questions around it. The interview is the most widely used method in qualitative research (Bell *et al.*, 2019; p. 434), which lets the interviewee(s) share their knowledge and opinions openly and flexibly. The interviewer can also seek extended discussions and probe and doubt the answers to uncover further details and open up new lines of inquiry (Meredith *et al.*, 1989).

In this research, following a well-documented interview protocol, interviews are conducted with eight experts in omnichannel order fulfillment and picking operations (with a minimum of three years of work experience) from three major UK retailers in the grocery sector, as well as two retail logistics service providers. Interviews, each 35-60 minutes, are face-to-face, online, or via telephone, and follow Yin's (2014) guidelines to *(a)* make sure the interviewees have a clear understanding of the research/interview purpose, *(b)* clarify the core and optional questions, and *(c)* uncover additional relevant points to discuss, if applicable. This helps the researchers to note the key steps of the fulfillment and picking processes, enhance their understanding of those processes in online and store channels, and reconfirm/add to the SLR's and industry investigation's outcomes. Whenever necessary, follow-up contacts have been made for further clarification of the answers. The interview questions focus on order fulfillment, consumer order receiving system, the picking process, back-store and shelf area operations, technology applications, special order requirements, waste management policies, inventory sorting and issuance procedures, and stock-out management guidelines. Power-quotes from the interviews and industry review are provided (Table I), to support the research statements and propositions.

Overall, the choice of interviewees, their understanding and knowledge of the research area, the number of interviews, and also the process of running interviews all support the internal and external validity and reliability of this stage of the research (Yin, 2014).

3.4. Numerical analysis

The outcomes from the SLR, industry investigations, and expert interviews (in the forms of statements/propositions) are tried out and examined through a numerical analysis using simulation. Simulation has proved to be a rigorous method for quantitative data generation and analysis, and enables a comparison of system performance while assessing the impact of numerous factors on the results (Chandrasekaran *et al.*, 2018). Simulation can analyze several scenarios to investigate the OCPI performance and the effects of various influencing factors. According to the research propositions (Section 4), the simulation focuses on OCPI performance in terms of product waste, lost sales, and freshness while analyzing the effects of influencing factors (channel effect, demand variability, product perishability, and shelf life visibility) on them.

The simulation of this study is designed in MATLAB R2019 (MathWorks®), which is cross-checked, debugged, and tested by two other simulation and programming experts. Full details of the activities and data flows in the physical OCPI system, their relevant analytical models, and the simulation process flow of the picking and ordering operations (of the OCPI system) are presented and explained in Section 5.

The simulation outcomes are further analyzed to find if the recommended propositions of this research are statistically significant or not. ANOVA is used to analyze the sensitivity of the results (impacts on waste and lost sales) to different levels of shelf life visibility, channel effect, demand effect, and product effects – in total, 52 experimental treatments are tested. The ANOVA test then compares the total mean (all treatments' mean) with each treatment's mean, to identify any significant difference in a defined confidence interval.

To analyze the differences between influencing factors, a k-wayANOVA has been performed and found significant interactions between the factors. In the presence of high interaction between the factors, following Groebner *et al.* (2018, p.494),one-way ANOVA is employed to test the levels of one of the factors against only one level of the other factor.

Table I. here

4. Findings: OCPI performance measures and influencing factors

The preliminary research findings for OCPI performance measures are shared in Subsection 4.1, and their influencing factors are explained in Subsections 4.2-4.5.

4.1. Order fulfillment process and performance measures

The main available channels for grocery consumers include shopping in-store and buying online, while the latter one offers consumers the choices of home delivery and click & collect (i.e. buy on-line, pick up from a collection point). Grocery picking for online consumers is done from the existing stores (also referred to as store-fulfilled, ship-from-store, and store-based) or from the fulfillment centers (i.e. dark stores). The store-fulfilled system has been the immediate choice of many grocery retailers and still dominates online grocery fulfillment (Carroll, 2020). It easily fulfills both *(i)* click & collect orders, collected by the consumer from the store or a nearby location, and *(ii)* home delivery orders, while each store has a dedicated coverage area. Picking for online consumers from the existing stores synergizes the store capacity and uses the same inventory for both online and store demands, hence benefiting from the pooling effect to mitigate demand fluctuations. The store-fulfilled system assures consumers of product freshness and quick delivery, while it does not need major investment in new warehouses and fulfillment centers. In sum, the benefits of this fulfillment model include faster delivery, lower shipment costs, higher in-stock probability, increased sales, and enhanced consumer satisfaction. In view of the points above, the OCPI systems of this research are treated as store-fulfilled, with two main channels/consumers: in-store shoppers and online shoppers.

For omnichannel inventory systems, a generic rule is to make the products available for consumers in all channels, but not to stock too many (Perera *et al.*, 2020). The objective is eventually cost/revenue optimization, considering purchase price, ordering, inventory holding, stock-out, and product waste as the main cost areas of inventory (including perishable inventory) systems - see the SLR summary outcomes in the supplementary file. Although the cost areas above dominate the literature, we argue (based on our findings) that not all of them are the most critical OCPI objectives. We then point out product lost sales, waste, and freshness as more relevant objectives (performance measures) for OCPI.

Ordering and inventory holding costs, which root in the Economic Order Quantity model and are still used in inventory models, have a lesser role in OCPI decisions these days. Fresh grocery inventories have high turnover and regular delivery in most omnichannel groceries, with well-established ordering processes including order placement administrative procedures, product shipment, and delivery.

Unlike single-channel systems, in OCPI, order placement and shipment are spread over multiple omnichannel entities – e.g. suppliers and distributors may receive orders from warehouses, dark stores, and retail stores. Such order placement and shipment procedures, with an overwhelming number of interactions among omnichannel entities are usually standardized and automated due to the need for swift ordering and fulfillment operations for perishable products. This helps the ordering process (i.e. identifying the order size, sending the order message, and making the payment) to be done with no or minimal time or resources. Apart from regular administrative procedures of each order, ordering cost is also driven by order delivery operations (i.e. receiving, unloading, and unpacking the arriving items). Those operations have considerably been expedited and automated in omnichannel systems - see the case of Tesco (GCCN, 2011) and Table I, quotes #3 and #21).

Moving toward more perishable products needs more frequent ordering by the omnichannel retailer to ensure the availability of fresh products for the consumers. Thus, a higher ordering cost might be expected. Those orders and their costs are, however, not key decision parameters for OCPI, if not totally negligible. Moreover, advanced information and digital technologies as well as handling and unloading innovations and technologies, developed for ordering and receiving processes of perishables (particularly for fresh foods) over the last two decades (e.g. Fikiin and Markov, 2014; Twede *et al.*, 2007), have made those operations standard, automated, fast and efficient. Hence, the cost per order is negligible, as indicated by Mahmoodi *et al.* (2015) for perishable inventories. Second, to ensure product availability and freshness, the retailer orders its perishable products very frequently (usually daily) anyway (albeit in different quantities), *regardless of the ordering cost*. Therefore, the ordering cost is not an input parameter affecting ordering decisions.

Ordering cost is also considered zero in recent studies on omnichannel systems of perishable products (Siawsolit and Gaukler, 2021). Building upon Gölgeci *et al.*'s (2018) argument for neglecting the ordering time in omnichannel supply chain systems, Xu and Cao (2019) discuss that the orders are delivered automatically and frequently (every day) to all omnichannel retailers, hence, they consider the ordering cost zero. This is reflected in the current research's interviews too (Table I, quotes #1,2,3). Therefore, contrary to traditional inventory models, in OCPI, the regular ordering process is not financially an issue, and the concern should not be about reducing the number of orders to minimize the cost.

Frequent delivery of perishables keeps the order size low (compared to less frequent orders of non/less-perishables). The unit value of the food products is also relatively low (e.g. compared to electronic, electric, or clothing products). Therefore, although no grocery retailer wants to hold excess inventory, the inventory holding cost of perishables is not what a grocery retailer is more concerned about. Instead, its focus is on product availability (see Table I, quotes #4,5). Omnichannel systems in particular focus on ensuring product availability for *ALL* channels (Cotarelo *et al.*, 2021; Ortlinghaus and Zielke, 2019). This is of greater importance for perishable items since their consumers rarely keep trying other channels, in case a product is unavailable in one channel. In omnichannel, specifically in store-fulfilled systems, like the OCPI system of this research, channels' inventories are shared, which can compensate perishability and lessen the inventory holding cost and the worries around it (Hajdas *et al.*, 2020; İzmirli *et al.*, 2021). Moreover, in OCPI systems, fresh items are ordered and made available in each channel, just before they enter sales/display shelves (Table I, quotes #22 and #23). In this vein, it is reasonable to consider the inventory holding cost insignificant (Venkateswaran and Augustine, 2013). Notably, transit inventories (common in OCPI systems, where fresh items are exchanged and moved between different omnichannel entities) are usually negligible too (Miao, 2014). Nevertheless, OCPI inventory reduction schemes primarily aim to reduce waste (mainly food waste), as elaborated further below.

Store space and product purchase price are other factors that affect the inventory cost. But the decisions about them are not technically made by the inventory planner – the former is calculated based on cost/m^3, related primarily to the store's location (which is decided strategically by the sales/market team), and the latter is agreed by the retailer's procurement team.

Stock-out or shortage is another key objective in inventory systems that may occur in the backlog or lost sales forms. Backlog lets the inventory system meet the demand in the subsequent periods if it faces stock-out in one period. OCPI systems, however, should deal with consumers who need the product almost immediately and cannot wait for their missing items to arrive later - only around 15% of consumers wait for backlogs (Bijvank and Vis, 2011). Instead, they usually choose a substitute product or shop. Hence, for OCPI, stock-out should be considered as lost sales (Table I, quote #6).

While product availability has always been a top priority for the retail sector (Browne, 2018), product stock-out is still a major challenge for groceries, as two-thirds of consumers report it at least sometimes in their fresh food shopping (Renner *et al.*, 2021), and it occurs in both online and store channels (Browne, 2018). In the grocery sector, these lost sales do not only apply to stock-out items but also to the whole product portfolio of the grocery retailer. After finding the shelf or his/her online basket empty of a particular item a few times, the consumer will feel that the items he/she needs are not often available in that specific store or chain, therefore he/she will switch to another store/chain permanently. Grocery consumers usually shop for the whole basket and not individual items, so they do not look around to buy a few items from different shops that have them available or offer them fresher – i.e. all-or-nothing situation (Renner *et al.*, 2021). Therefore, the real cost of stock-out for one item can go far beyond losing sales for one item on one occasion. The cost is losing the consumer's entire order and probably the consumer permanently - over 20% of grocery shoppers switched to a competitor last year in frustration over item unavailability (Getz, 2021). Meanwhile, the perishable grocery market becomes more omnichannel (e.g. more than two-thirds of consumers buy at least some fresh food online – Renner *et al.*, 2021). Omnichannel consumers are technology savvy to find their new shop quickly, are more flexible to adapt to a new channel/shop and have more options to switch to and buy from, in the case of stock-out in a channel. Hence, minimizing stock-out in the grocery omnichannel is of even greater importance than before – i.e. conventional bricks & mortar retail dominant era.

As crucial as lost sales, overstock is a significant challenge for groceries, since it leads to product waste - which has economic, social, and environmental implications. Every year around 930 million tons of food are wasted, and the retail sector contributes to 13% of it (UN, 2021), while the waste can amount to 1-2.5% of the retailer's turnover (Horoś and Ruppenthal, 2021). Extra perishable stock, leading to waste, causes substantial disposal costs. Akkaş (2019) indicates that on average expiration cost of an item is about five times the gross profit of the item, and spoilage is a major cost driver of perishables (Siawsolit and Gaukler, 2021). Even pricing down and selling the expiring items to avoid disposal costs cause high operational costs owing to finding, sorting, and labeling these items. More importantly, waste, particularly food waste, typically undermines an organization's social responsibility.

Waste and lost sales are negatively correlated with each other too. Due to the demand variability and short product shelf life of perishables, reducing the lost sales cannot be easily achieved by increasing the order size to suppliers. Product perishability prevents the extra quantities, ordered to meet future fluctuating demand, from surviving on the shelf – they instead lead to higher waste. Likewise, minimizing waste by ordering fewer products causes a higher level of lost sales. Moreover, implementing a FIFO sales system to reduce waste is not very straightforward - in-store consumers usually pick the fresher items, and online consumers continue to buy online if they receive fresh items with long shelf-lives (Önal *et al.*, 2015).

In view of the points above, the OCPI costs are largely driven by waste and lost sales, but at different rates and significance levels in different channels – e.g. an expiring item in-store can be priced down in the last few hours of its shelf life to encourage some demand, whereas a soon-expiring item sold online is very likely to be rejected by the consumer, while the item has no time to be sold in store. On the positive side, potential synergy among the channels encourages them to support each other to reduce waste and lost sales (e.g. by offering older items in-store and fresher items online).

The transaction cost theory explains how pricing-down the near-expiration items (mostly applicable to in-store consumers) reduces the bargaining cost of the store channel, while the same channel has a higher searching cost for its consumers. The online channel, on the other hand, have higher inspection cost for the consumer (to check the product's freshness and appropriateness). These indicate the complex impact of the channel on OCPI transaction costs, hence on the channels' demand mix, and eventually on waste and lost sales. This implies that in the grocery retail, costs of both waste and lost sales are considerable for both channels – i.e. a retailer cannot simply shift the stock from one channel to the other to keep consumers of one channel happy with a presumption that the other channel's consumers become less upset. Therefore, it can be concluded that:

Statement 1: Waste and lost sales are the OCPI's core (and negatively correlated) performance measures, to be minimized in both store and online channels.

The OCPI's waste and lost sales are highly related to consumer picking behavior or expectation of product freshness. The demand age-dependency has been increasingly addressed in the recent perishable inventory management literature (e.g. Deniz *et al.*, 2020; Dobson *et al.*, 2017 – please see the supplementary file for the full list). For example, Tsiros and Heilman (2005) show how consumer willingness to buy a product declines linearly (for products such as carrots and yogurt), or even exponentially (for chicken and beef), with the product's remaining shelf life. Consumer sensitivity to product age is nevertheless diverse (Herbon, 2014), and this research finds them notably different in store and online channels.

For in-store consumers, there are various product picking behaviors reported in the literature. Dobson *et al.* (2017) and Chen *et al.* (2021b) point out that different in-store consumer groups have different thresholds of product freshness acceptability, while Lowalekar *et al.* (2016) consider the in-store consumers' freshness preferences random. More empirical data also indicate that not all in-store consumers search for and pick the freshest items – e.g. while 70% choose the freshest milk available, 23% pick the item when it is near expiration (Shah *et al.*, 2016). Almutairi *et al.* (2022) also show that one-third of grocery in-store consumers do not look for the expiry date on the product label. Moreover, in-store consumers may be pushed or encouraged to pick the less fresh items by the store, moving older items to the front and fresher ones to the back of the shelf, or employing dynamic pricing techniques (Formentini and Romano, 2016). Thus, in-store picking can be considered dispersed among various consumer types, labelled by this paper as "fresh-pickers", "random-pickers", and "expiring-pickers".

Online consumers are, however, quite different and generally need long shelf life for a fresh item (Mkansi *et al.*, 2018; Singh, 2019). Their desire for the freshest product is related to their shopping frequency, and the fact that the lesser the shopping frequency, the longer the product should survive at home. Therefore, consumers do not typically accept a soon-expiring item (not because they seek the luxury of a very fresh item but because they need to keep it till their next delivery, usually in a week or two). In other words, online consumers buy more (online consumers have 30-60% more valuable shopping baskets than in-store shoppers (Skulocal 2018)) and keep it for longer. Quotes #7-11 in Table I indicate several cases of frustration over receiving near-expiry-date items, which have led the online consumer to change his/her retailer.

The online consumer's demand for product freshness is expected to be the same in both home delivery and click & collect channels. The main motive to shift to online shopping is convenience (Deryan, 2022) and consumer reluctance to go inside stores (NCR, 2021), since in-store shopping is widely regarded as time-wasting and tiresome (Pernot, 2021; Vyt *et al.*, 2022). Of online grocery shoppers, those who prefer more flexible delivery time slots, or need to have the products quicker (e.g. on the same day or next day), or want to avoid paying for home delivery, while still hesitate to shop in-store, generally choose the click & collect option (Ketzenberg and Akturk, 2021; Redman, 2022; Silverstein, 2021; Wilson 2021) – i.e.they do not primarily choose the click & collect option to have a visit of the store as well. It should be noted that the click & collect pickup points are not necessarily within the store, and they are usually located outside the store or in a separate, stand-alone location (Gielens *et al.*, 2022; Morganti, 2019; Visser *et al.*, 2014; Vyt *et al.*, 2022) – i.e.in-store visit is not an immediate offer of the click & collect channel.

Even those consumers who choose the click & collect option to be able to visit the store and buy/exchange the missing or less fresh items that they might receive at the collection point (Gielens *et al.*, 2022) still have the expectation of high product freshness. So, if they go into the store, they will pick the freshest items – i.e.in terms of picking behavior and expectation of product freshness they are similar to online consumer category who buy more/fresher and keep it for longer.

In view of the theoretical/empirical evidence and the discussion above, it can be stated that:

> **Statement 2:** Related to waste and lost sales, product freshness is the third key OCPI performance measure. While in-store consumers' preferences toward perishable item freshness are diverse (including "fresh-pickers", "random-pickers", and "expiring-pickers"), online consumers consistently prefer fresher items.

Statement 2 can also be viewed through the transaction cost theory lens (Klein *et al.*, 1990). Considering the heterogeneous consumer preferences/marginal valuations across different channels and their related transaction costs (e.g. search, bargaining, monitoring, and safeguarding), transaction cost theory can explain how the perishable product's consumer demand for freshness is influenced by the channels and their transaction costs. Store shoppers usually spend some time finding the right, fresh products, which can meet their desired product shape, freshness, and shelf life (search cost). They may also evaluate the product against their offered prices and accept less-fresh products with a lower price (bargaining cost). Online consumers may have lower search and bargaining costs, since they mainly rely on the information provided in the e-tail shop, and do not have fresh products physically in front of them to search and evaluate one by one. However, online consumers need further checks on arriving items to make sure their freshness and features match what was promised online – and ask for a return and refund if they do not (monitoring and safeguarding costs).

The three performance measures, i.e. product waste, lost sales, and freshness, are related to each other and chiefly affect OCPI decisions. A comparison of the significance of inventory costs across OCPI and other systems (i.e. single-channel and non-perishable products) is provided in Table II.

Table II. here

4.2. Channel effect

Based on Statement 2, the OCPI system should consider diverse consumer expectations of product freshness since they have implications for product picking (e.g. picking the oldest first or the freshest first) by the consumer or the retailer's picker. It, in turn, affects the waste and lost sales measures.

Mkansi *et al.* (2018) indicate that online consumers of perishables prefer to receive fresh products with the longest possible shelf life and dislike (and even reject) soon-expiring items. Thus, a minimum shelf life is usually promised to online consumers. To ensure that the minimum shelf life is delivered (and moving even further to keep the consumer happy), items with the longest-available shelf life are picked for online consumers. This is reiterated by the leading supermarkets' online fresh product sales policies and procedures (Table I, quotes #12-15 and 24).

As per Statement 2, not all of the store channel consumers insist on the freshest products. The store can make older items to be picked more by placing them on the shelf-front or pricing them down. It implies that the omnichannel system has more bargaining options, as per the transaction cost theory (as explained in Section 1), to convince its in-store consumers to buy items with a shorter remaining shelf life.

The online and in-store picking policies lead to different remaining inventories on-hand: older (less-fresher) items for the former and mixed items with various shelf-lives for the latter.

Older inventory on-hand, which is technically not counted for the online channel and is less favorable for at least some in-store consumers, has a higher chance of reaching the expiry date on the store's shelf (i.e. waste). Meanwhile, by insisting on fresh items and rejecting less-fresher ones (particularly the soon-expiring items), the online channel limits its available inventory which increases its chance of facing lost sales.

Therefore:

> **Proposition 1:** It is expected that by increasing the share of online demand, of total demand, the waste increases. Similarly, due to the high expectation of online consumers for fresh products, just a proportion of the total inventory on-hand is acceptable by them, which increases the chance of the OCPI system facing lost sales.

It should be noted that the solution is not simply placing bigger orders and carrying more inventory since product perishability may cause even more waste. Hence, the effect of the online channel on OCPI performance (i.e. the higher the online share, the higher the waste and lost sales) should be examined considering other factors, as follows.

4.3. Demand variability effect

Demand variability refers to the volatility and dependence of the grocery demand on various factors such as weather (changes beyond seasonality, which might be different for different channels even on the same day), social trends (largely unpredictable; e.g. due to social media effects), pandemics, national/international events, available inventory, and performance and promotion of competitors (Li *et al.*, 2015; Taylor and Fearne, 2009). Therefore, although the total grocery demand, annual and even seasonal, can be forecasted, the day-to-day demand in its different channels may face frequent fluctuations. Omnichannel systems benefit from sharing inventory for multiple channels to absorb the demand shock in one channel using the other channel's inventory (i.e. pooling effect). However, higher, unpredictable demand fluctuations in perishables can still cause significant waste and lost sales (Chen *et al.*, 2021a) - also see Table I, quotes #16-18.

The problem lies in the inability of the inventory system to meet the demand, since the extra stock, ordered to manage the demand fluctuation, becomes obsolete before it can buffer against the changing demand. Moreover, since the consumers' expectations using OCPI's channels are heterogeneous, responding to unexpected changes in their demands is more problematic than single-channel or multi-channel systems. High demand variability also makes it difficult for the retailer to offer the freshest product to those consumers who insist on freshness (e.g. online consumers).

This indicates that the adaptability of a complex OCPI system to the dynamic, diverse demand is significantly reduced when the demand variability increases. Hence:

> **Proposition 2:** Demand variability has a negative impact on waste, lost sales, and product freshness (i.e. the higher the demand variability, the higher the waste and lost sales, and less fresher products are offered to consumers). This impact may, however, vary depending on the share of the store and online channels of the total demand.

4.4. Product perishability effect

After being produced, perishables need to be consumed within a limited time period, called shelf life, which is fixed or variable (Goyal and Giri, 2001). The fixed shelf life considers shelf life *a priori*, indicating a certain time period till the product can be sold and consumed. Examples include packaged fresh food (Muriana, 2016), blood products such as platelets (Abbasi and Hosseinifard, 2014), and medicines (Chung and Kwon, 2016). The majority of perishable inventory planning models are developed based on the fixed shelf life assumption for the product (Muriana, 2016). The variable shelf life applies to products whose usefulness diminishes over time, and their deterioration depends on less controllable conditions such as the individual item's unique attributes. Examples include bulk fresh fruits, vegetables, and flowers (see the supplementary file for a list of different types of shelf-lives).

Short shelf life in OCPI systems makes inventory management more challenging than non-perishables since it enforces major constraints, such as the maximum cycle inventory and storage time, to the inventory holding and planning system. Largely connected with the channel effect, product shelf life affects the stock-keeping decisions in different channels, thus the OCPI performance is expected to be sensitive to product shelf life (Table I, quote #19).

Hence, the product's shorter shelf life considerably affects the OCPI's adaptability. It gives less time to the OCPI system to hold sufficient inventory to respond to sudden increases in demand or interruptions in supply. The shorter shelf life may also prevent OCPI from switching products between channels or prioritizing one over the other. The significance of the shelf life effect on waste and lost sales in OCPI systems can be more substantiated when the channel effect is considered too (e.g. sending the freshest products to online consumers). On the one hand, the shorter shelf life makes it difficult for OCPI to satisfy more demanding channels (leading to lost sales). On the other hand, by providing fresher items to more demanding channel(s), the remaining items are wasted due to the shorter shelf life. (Table I, quote #20).

Therefore, it can be stated that:

> **Proposition 3:** Product perishability has a negative impact on waste, lost sales, and product freshness (i.e. the shorter the product shelf life, the higher the waste and lost sales, and the less-fresher products are offered to consumers). This assertion may vary depending on the share of the store and online channels of the total demand.

4.5. Shelf life visibility effect

Further challenges in managing the perishables include the stock shelf life visibility. The stock level status is typically reviewed periodically or continuously, and the ordering policies are set accordingly. In the retail sector, the sales data which are captured at the point-of-sale can facilitate a continuous review of the stock level and trigger the order automatically. OCPI systems, however, need to look at further details of inventory data. In a typical inventory ordering/fulfillment system, although the shelf life of the items, received from suppliers, is known at the SKU (stock-keeping-unit) level (Schneider and Klabjan, 2013), when they are put on the shelves as individual items, different items with different shelf-lives will be mixed, and the point-of-sale system does not capture the shelf life of each item sold. Hence, while the inventory system knows how many items it holds, it does not know for how many days each of them can survive. Haijema and Minner (2019) point out the benefits of inventory-age data in a single-channel system. Nevertheless, item-level data are crucial to an omnichannel system, as it needs to define how to allocate and pick items (e.g. FIFO and LIFO) for each channel to satisfy its consumers' particular expectations (channel effect). This consequently affects the stock availability and ordering policy, where the updated stock shelf life data, at the item level, can be helpful to provide the right level of product availability.

In line with the complex adaptive system attributes (as addressed earlier in Section 1), an OCPI system has numerous entities/agents (e.g. distribution center, warehouse, retail shop, and delivery system), which hold large amounts of heterogeneous dynamic inventory data. The data are dynamic since the inventory level at each location and their shelf life statuses are frequently changing. They are heterogeneous since various products are subject to different rates of perishability, and shelf life data may vary at the individual item level, depending on the product's packaging or handling conditions or consumer picking behavior. These features make OCPI a complex system, where its capability in managing order fulfillment and possible switching of products from one channel to another, to respond to changing consumer demand, supports its adaptability as a complex adaptive system. The OCPI adaptability largely depends on its ability to capture real-time inventory data accurately (i.e. individual item's shelf life data), which can be supported by means of more sophisticated barcodes, smart tags, radiofrequency identification (RFID), or cyber-physical systems. This higher level of inventory visibility and adaptability positively contributes to the OCPI's performance in terms of waste and lost sales:

Proposition 4: Shelf life data visibility at the item level positively contributes to the OCPI performance; and should be considered in the presence of channel, product perishability, and demand variability effects.

5. Testing propositions - numerical analysis

5.1. OCPI order fulfillment process simulation

The research's statements and propositions are numerically analyzed via Monte Carlo simulation modeling based on the following assumptions and inputs:

- The model includes one product and one retailer with two channels: online and store. Consumers either buy online and receive their orders at home or buy from the store. No picking, by the consumer, from the store is considered in the case of online purchasing.
- Demands of both channels are fulfilled from the same store-fulfilled inventory.
- The unit of time is day.
- Items arrive from the supplier at the beginning of each day.
- Supplier capacity is considered unlimited.
- Items are considered highly perishable (shelf life<5 days)
- Items are available to be picked up as soon as they arrive from the supplier.
- All arriving items have a fixed shelf life of $S_{max} \in N$ indicated in days.
- Items with different shelf-lives are mixed up in the inventory system (on the store's shelves).
- The model includes ordering and consumer picking operations. Ordering is done based on the daily review of the stock level at the end of each day and follows (r, S) policy. The order size in day t ($Q(t)$) equals average demand times lead-time minus inventory on-hand.
- Picking is channel dependent. Among in-store consumers, some pick the freshest items, and some simply pick any accessible item including the oldest ones, pushed to the shelf-front by the store personnel. Hence, it is assumed that in-store consumers pick items randomly. Online consumers expect to receive fresh items, therefore, in the picking process, the

freshest available items (those with the longest shelf-lives) are picked for online consumers (see Subsection 4.2 for details).

The simulation of this research follows the main steps of receiving, issuing, picking, recording, and ordering in the OCPI system, as illustrated in Figure 2a. It then executes the simulation formulations of Figure 2b. The Figure 2b loop is reiterated for T=180 days for 1000 rounds. This process repeats for 54 scenarios, which are designed based on different levels of the OCPI influencing factors as follows:

- Channel effect is assessed based on the share of online and in-store demand of the total demand. Their states are identified as: *(i)* store-dominant, where the store and online have 80% and 20% shares of the total demand, respectively; *(ii)* balanced-share, where each channel has 50% share of the total demand; and *(iii)* online-dominant, where store and online have 20% and 80% shares of the total demand, respectively.
- Demand effect is assessed based on variation in demand, shown by the coefficient of variation (CV) at three states: low variation represented by CV=0.5; medium variation represented by CV=1; and high variation represented by CV=1.5.
- Product effect is assessed based on its perishability (S_{max}), at three levels: *(i)* shelf life=2 days; *(ii)* shelf life=3 days; and *(iii)* shelf life=4 days.
- Shelf life data visibility is considered in two states: *(i)* item-level data, where the inventory system knows how many of each item, with exact remaining shelf life, is on-hand; and *(ii)* aggregate-level data, where the total inventory on-hand is known, but it is not clear how many of the products will expire on day t, $t+1$, or later.

Figure 2. here

In each of the 54 scenarios above, to remove the effect of ordering/lot-sizing policy on the results, order sizes in a range of ±30% of $Q(t)$ (named order coefficient) are tried (0.70*$Q(t)$, 0.72*$Q(t)$, …, 1.28*$Q(t)$, 1.30*$Q(t)$; totaling 31 points). Therefore, the simulation results in a total of 1674 data points: 54 scenarios, each of them with 31 waste/lost sales performance data (for 31 order sizes). Figure 3 illustrates the results of a simulation, runs for T=180 days and

1000 rounds, for a normally distributed demand with a mean μ=100, and σ^2= 2500, 10000, and 22500 (resulting in CV$\in\{0.5,1,1.5\}$), and $S_{max}\in\{2,3,4\}$. Online share of total demand$\in\{0.2,0.5,0.8\}$, and delivery lead-time L=1 (i.e. the next day delivery from the stock depo or supplier to the retailer, which reflects the real-life situation where almost all fresh perishable items are delivered on the next day morning if they are ordered by the afternoon).

5.2. Simulation results

In Figure 3, graphs from left to right and top to bottom show changes in the shelf life (from 2 to 4) and online share of total demand (from 0.2 to 0.8) respectively. Each scatter graph includes three pairs of data; each pair represents the performance (waste and lost sales) for a level of CV<1 (0.5), CV=1, and CV>1 (1.5). Each point of the scatter graph represents the overall average number of waste and lost sales (out-of-stock) items for the R runs and T days of the simulation for each order coefficient. For example, the points of the top-left graph of Figure 3 show for online share = 0.2 and shelf life (S_{max}) = 2 how by increasing the order size from 0.7xQ to 1.3xQ, from left to right, the waste is increasing and lost sales (Out-of-Stock) is decreasing. In the top-left graph, in the circled area (CV=1.5), the graphs with □ and ∗ shapes show the situations when item-level shelf life data "are not" (shown by ALD in Figure 3) and "are" (shown by ILD in Figure 3) known respectively. Other shapes are used for CV=0.5 and CV=1.

Figure 3. here

The following assertions are made from the initial analysis of Figure 3:

- Increasing the shelf life visibility to item level improves performance measures in general, but its details should be investigated.
- By increasing the online share in the total demand, the improving role of item-level shelf life data on both performance measures becomes less significant.
- By increasing the demand variation (CV) both waste and lost sales worsen.
- By increasing the product shelf life (S_{max}) product waste improves.
- Product freshness slightly improves by increasing the share of online demand – mainly due to the picking policy.

The initial assessments above are subject to further detailed analysis as follows.

5.3. Significance of the influencing factors

Following the experimental design, described in Subsection 3.4, each effect (on waste and lost sales) of the channel (store-dominant, balanced-channels, online-dominant), demand variability (high: CV=1.5; medium: CV=1; low: CV=0.5), and product perishability (shelf life S_{max}=2; S_{max}=3; S_{max}=4) is assessed while two others are fixed. The results are shown in Figure 4a. The effect of shelf life visibility is assessed for two scenarios of data availability at aggregate and item levels, while three other factors are changing (in total 3x3x3=27 combinations, demonstrated in detail in Figure 4b). Accordingly, the significance of the research's propositions is elaborated:

Proposition 1/Channel effect (Figure 4: *Box I & II*) is not supported for lost sales, but partially supported for waste (for longer shelf-lives and lower demand variabilities, i.e. the channel effect on waste is sensitive to shelf life and demand variability).

Proposition 2/Demand variability effect (Figure 4: *Box III & IV*) is fully supported, i.e. demand variability has a negative impact on waste and lost sales.

Proposition 3/Product perishability effect (Figure 4: *Box V & VI*) is partially supported, for the impact of product perishability on waste, but not on lost sales.

Proposition 4/Shelf life visibility (Figure 4: *Box VII, VIII & IX*) is partially supported. Item-level shelf life visibility has a positive impact on lost sales, but only for the highest level of product perishability (S_{max}=2). It improves the waste in store-dominant and balanced-channels for all shelf-lives and demand variabilities (except for higher demand variabilities and the shortest shelf life – see Figure 4 *Box IX* for details).

Figure 4 here

6. Discussions and Conclusions

6.1. Theoretical implications

The research contributes to the literature by arguing that, unlike conventional inventory systems, OCPI should boost three distinctive performance measures: product waste, lost sales, and freshness. Driven by the main features of OCPI (around product perishability and multiple channels of sales/delivery), four factors influence OCPI performance: channel, demand variability, product perishability, and shelf life visibility. The factors are interconnected while their effects on OCPI are diverse.

In the channel effect, different consumers (in-store vs. online channels) have different impacts on waste. The impacts are moderated by demand variability and product perishability. This result does not totally support those of He *et al.* (2019) who claim that more share of the online channel should reduce the circulation loss of fresh produce items. However, their recommendation for the online channel with a "presale" business model can be added to the OCPI systems of this paper to reduce waste of perishable products.

The channel effect does not have a significant impact on lost sales – i.e. by shifting toward online channels (which demand fresher products) the OCPI system does not face a higher lost sales risk. Such an advantage can be traced in the omnichannel's capability of moving its fresher stock from the store channel to the online channel. This type/level of adaptability is a key for OCPI as a complex adaptive system and necessitates the integration of inventories. This result can be further studied in connection with consumer satisfaction theories and the recent discussion by Du *et al.* (2019) on the role of stores in managing online consumers' disappointment, which occurred due to unavailable products for home delivery.

High demand variability considerably exacerbates waste and lost sales in all channel and product shelf life scenarios. This requires further focus on demand management. Lan *et al.* (2018) show that high demand uncertainty triggers collaborations among key players of a dual-channel system (e.g. between online and offline distributors), which helps the system manage demand variabilities. We agree that such collaboration should exist in an adaptable OCPI system. Hence, Lan *et al.*'s (2018) collaboration idea should be tested for perishable products and further investigated in terms of their recommended demand uncertainty threshold to prompt collaboration.

Product perishability negatively affects waste for all demand variability and channel scenarios. This emphasizes that avoiding waste needs product design teams to work on extending the perishables' shelf-lives and the operations teams to ensure adequate (e.g. temperature-controlled) storage conditions for perishable items.

Our results reveal that product perishability has no significant effect on lost sales, which can be interpreted as the high adaptability of the omnichannel to manage inventories. This outcome can be coupled with recent retail network studies (Belavina, 2021) that show the relationships between grocery stores' density and food waste.

Higher shelf life visibility helps reduce waste, particularly in store-dominant and balanced-channels. This is in line with earlier stress on more comprehensive and detailed inventory data for perishables (Bakker *et al.*, 2012; Hill, 2007; Janssen *et al.*, 2016), but this research finds much further detail on the OCPI performance sensitivity to the shelf life visibility. Shelf life visibility does not considerably improve waste in the online-dominant case, where the consumer expectation for product freshness is so influential on inventories that more visibility of shelf life data cannot reduce waste that much. Shelf life visibility reduces lost sales of highly perishable products (S_{max}=2). The OCPI's capacity to manage lost sales when S_{max}=3&4 makes it less sensitive to shelf life data visibility. These findings on shelf life visibility urge stock-age-based inventory models (Bakker *et al.*, 2012; Janssen *et al.*, 2016; Haijema and Minner, 2019) to be revised for online channels with different levels of product perishability.

Figure 5 summarizes the outcomes of this research, demonstrating how waste and lost sales are influenced by channel, demand variability, product perishability, and shelf life visibility – the former two are labeled as market-driven factors and the latter two are labeled as operations-driven factors, reflecting the OCPI's interface with both market and operations. Figure 5 also shows how the influencing factors moderates each other's impact on the OCPI performance.

Figure 5. here

6.2. Managerial implications

This research has several practical contributions, which inform retail operations, supply chain, and logistics decisions. For grocery business and operations managers, it is imperative to hold the right amount of inventory for each channel at the right time, while deviations from it may lead to product waste or lost sales: both crucial for retail operations and market performance. The outcomes of this research indicate that product freshness is a market qualifier for an OCPI system, achieving it has implications for the system's waste and lost sales.

Consumer expectations of product freshness differ depending on the channel and might be manageable in different ways while controlling product waste and lost sales. This research discusses that the solution is not just with the operations managers to deliver the freshest items to more demanding consumers or with the marketers to manage the consumer expectations to accept less-fresher products, but also in managing demand variability and shelf life visibility. The response to demand variability can be proactive (attempting to reduce it through various marketing and sales techniques, e.g. promotion and dynamic pricing). Besides, operational contingency plans (e.g. flexible resources) can build a good reactive capability for OCPI to handle lumpy demands or short-term market slowdown.

At the same time, technical progress is needed to increase the product shelf life visibility. Although, the higher visibility may look better for inventory systems, given the major cost of the required technologies for it (e.g. RFID, smart tags, smart cameras, or cyber-physical systems), it is necessary to have a clear view of the impacts of item-level shelf life visibility on OCPI performance. The findings of this research indicate that moving from aggregate to item-level data visibility does not necessarily and immediately lead to lower waste or lost sales. The impact is lower in the online channel and is higher for highly perishable products.

6.3. Future research

Future studies should test the outcomes of this paper with empirical data. The recommended structural model of Figure 5 can be a basis for further hypothesis testing. Moreover, the investigation of a wider range of options for the OCPI influencing factors, identified by this research (e.g. a wider range of shelf-lives, or a greater choice of channels) is called for. Future research can also incorporate dynamic shelf life where the freshness of a product is not a linear function of time as is the case for some meat and fruit products. Some retailers started to remove best-before dates from products such as peppers or potatoes to encourage customers to buy without considering freshness explicitly. The impact of this decision by retailers on consumers' preferences and OCPI operations is worthy of further investigation.

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Table I. Power quotes of the interviews and the industry documents.

#	Quote	Interviewee # or the source
1	"an EDI-based system works for us very well and links us with the suppliers. Most of the regular orders and deliveries are handled by that system…"	2
2	"automated ordering and replenishment systems have made the whole ordering process seamless and efficient … mistakes and errors are relatively low too so less manual intervention is needed, and we save money in this part of the business"	3
3	"When the product and the supplier are approved, we will not spend that much time for the ordering and receiving process and not worry about it - since most of it is straightforward, well-standardized, and automated."	4
4	"It is all about shelves and making sure they are full"	4
5	"I see online customers are really upset when they see missing items [unavailable] in their list. … for most products, we order and keep extra stock to avoid any shortage."	3
6	"We simply lose the customer to our competitors if he faces empty shelves"	4
7	"Agnes has a chronic illness and relies on groceries being delivered to her home. She said she's been 'put off buying online' by the issues [receiving less fresh items] she has experienced."	(Calnan, 2021)
8	"[the customer] had to go to Asda himself after receiving bread and milk at 9.15pm with use-by-dates of the following day … [the customer] no longer shops at Asda."	(Calnan, 2021)
9	"Tracey Vincent, 46, from Stanhope in Ashford, said she regularly buys up to £100 worth of groceries from Tesco. But her mood soured after repeatedly being sent items such as yoghurts and bread with little time left to run on the sell-by dates. She added: 'I've stopped shopping with Tesco now.' "	(Barlow, 2017)
10	"[the customer] got in touch with Sainsbury's on Twitter to share what had happened [receiving a product that reached its use-by date the same day she received her shopping] and the supermarket responded with a link outlining its Short Shelf Life policy. … 'I no longer shop there,' said the customer."	(Calnan, 2021)
11	"Abby Skipper from Belfast ordered a fruit platter for her son's birthday, but its use-by date was just one day after the delivery took place. This meant it was inedible by the time the party came around, two days after she received her items."	(Calnan, 2021)
12	"Our pickers work hard to ensure that the products they choose are well within their use-by dates so our customers get the freshest produce available."	(Calnan, 2021: Asda)
13	"… they [customers] will always receive the freshest possible produce available."	(Calnan, 2021: Sainsbury's)
14	"Customers can ensure they get good dates on their groceries, … pickers aim to provide the longest expiry dates in store."	(Calnan, 2021: Tesco)
15	"Pickers are told to select items with the longest date available when choosing products. Any items with the same use-by date as the delivery date will be given to customers free of charge."	(Calnan, 2021: Waitrose)
16	"Fresh salads and sandwiches sell more during the weekdays [compared to weekends], but we have seen some weekends, particularly in summer when the shelves become empty in the morning, possibly because of the good picnicking weather."	5
17	"For these [highly perishable] items, a retailer cannot keep the stock separate for online and store customers. So one may take the share of the other. … When they sell good, there will be no waste."	6
18	"Some product lines, even the very vulnerable ones like raspberry, are OK since they have a fairly stable demand. The waste is in more ready-to-eat salads … if their demand is less than average…. The lost-sales, I think, happens to the sandwiches when we see a big jump in demand"	3
19	"These products have a very short time to stay on the shelf. It does not matter how many we order on Monday. They cannot survive by the weekend and should be disposed if we cannot sell them."	2
20	"We pick the freshest ones for online customers, [which] means that the rest will end up in the bin in a day or two [if they are not picked by the store consumers]."	4
21	"… unloading pallets is very much standardized in all delivery sites and stores…. This speedy process is the result of many years of efforts and works with supplier to improve their palletizing and packaging operations in order to speed up the unloading and unpacking operations at the delivery point."	4
22	"We operate a Just-in-Time systems. So the products in all channels, arrive when we need them, …, the day after we order them."	1
23	"Our replenishment system places the orders according to its prediction of the demand trend [for weekdays and weekend] … and orders, for example sandwiches, arrive in the morning, except on Sundays, according to the expected demand for that day."	5
24	"customers are promised that the products they buy will have a minimum amount of time at home before they expire. This commitment to offering customers the most time possible to enjoy their food, means that Ocado sometimes has fresh, edible products they will not sell to their customers."	(Ocado, 2018)

Table II. Inventory costs significance: an indicative comparison of OCPI with other systems.

Inventory System Costs	Inventory types, classified according to the shelf-life and channel range			
	Single-channel, non perishable	***Omni-channel, non-perishable***	***Single-channel, perishable***	***OCPI***
Product Freshness	N/A	N/A	Significant	Significant
Product Waste	Not a major issue	Not a major issue	Significant	Significant
Stockout (Lost sales)	Significant, if applicable	Significant, if applicable	Significant	Significant
Stockout (Backlog)	Significant, if backlog is acceptable	Significant, if backlog is acceptable	Insignificant, since backlog is not acceptable	Insignificant, since backlog is not acceptable
Purchase Price	Significant, when quantity discount is offered	Significant, when quantity discount is offered	Insignificant, since quantity discount does not usually apply	Insignificant: since quantity discount does not usually apply
Inventory Holding	Significant	Mostly significant: depending on product value, and inventory sharing among channels	Somehow significant: inventories have high turn-over but should be sold only through one channel (often a costly location/store)	Insignificant: inventories are shared among channels, and have very high turnover
Ordering	Significant	Mostly significant: depends on the delivery logistics, and ordering process. Compared to perishables, these product needs less-frequent delivery.	Somehow significant: ordering procedures are mostly automated, but delivery/receiving operations are costly (partially/mostly manual)	Insignificant: multi-channel ordering process, and perishable product delivery operations are very frequent and highly automated with no cost.

Methods	**Outputs**	**Cross-referenced section in the paper**
Systematic Literature Review (SLR), Industry Investigation & Expert Interviews	OCPI Performance Measures and Influencing Factors Theoretical formulation of the influencing factors' impacts on OCPI performance measures: *Statements 1 & 2 - Performance measures* *Proposition 1 – Channel effect* *Proposition 2 – Demand Variability effect* *Proposition 3 – Product Perishability effect* *Proposition 4 – Shelf life Visibility effect*	*Section 4*
Numerical Analysis	Simulation procedure, Significance levels of the influencing factors impacts on OCPI's performance measures	*Section 5*

Figure 1. Summary of the research methods and their outputs.

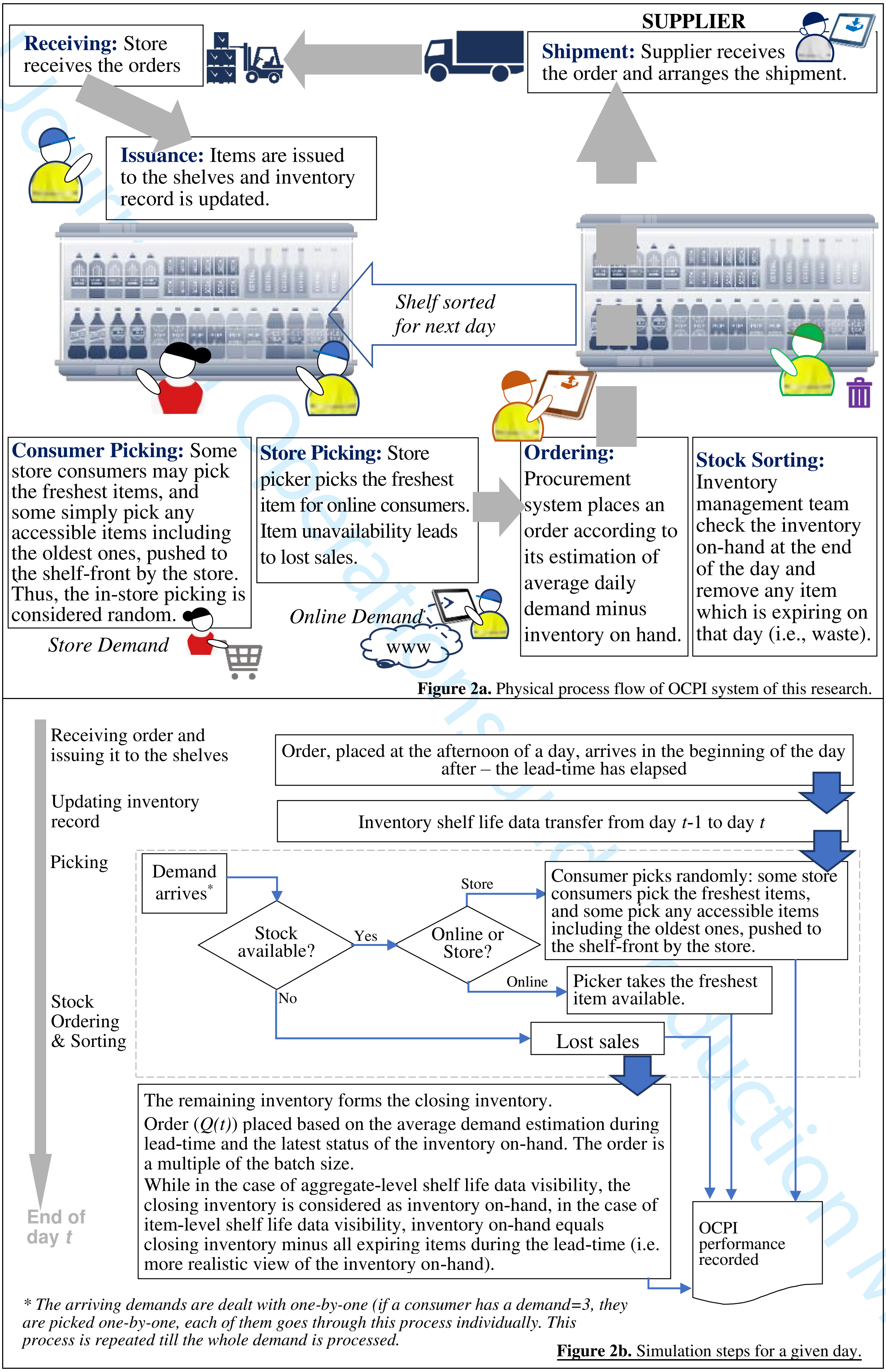

Figure 2. Order fulfillment procedure for store and online channels.

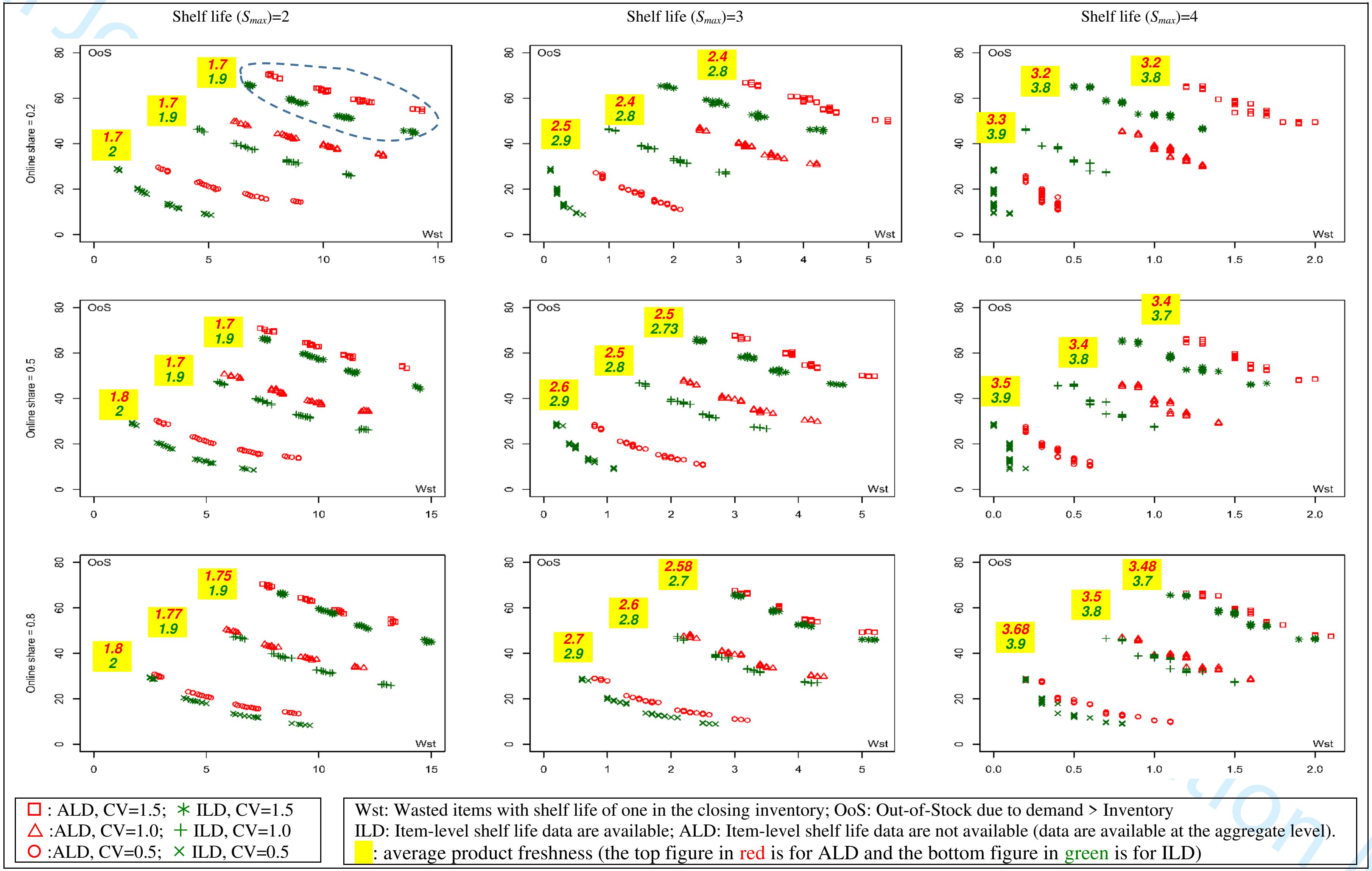

Figure 3. Simulation results for 27 scenarios and two shelf life visibilities.

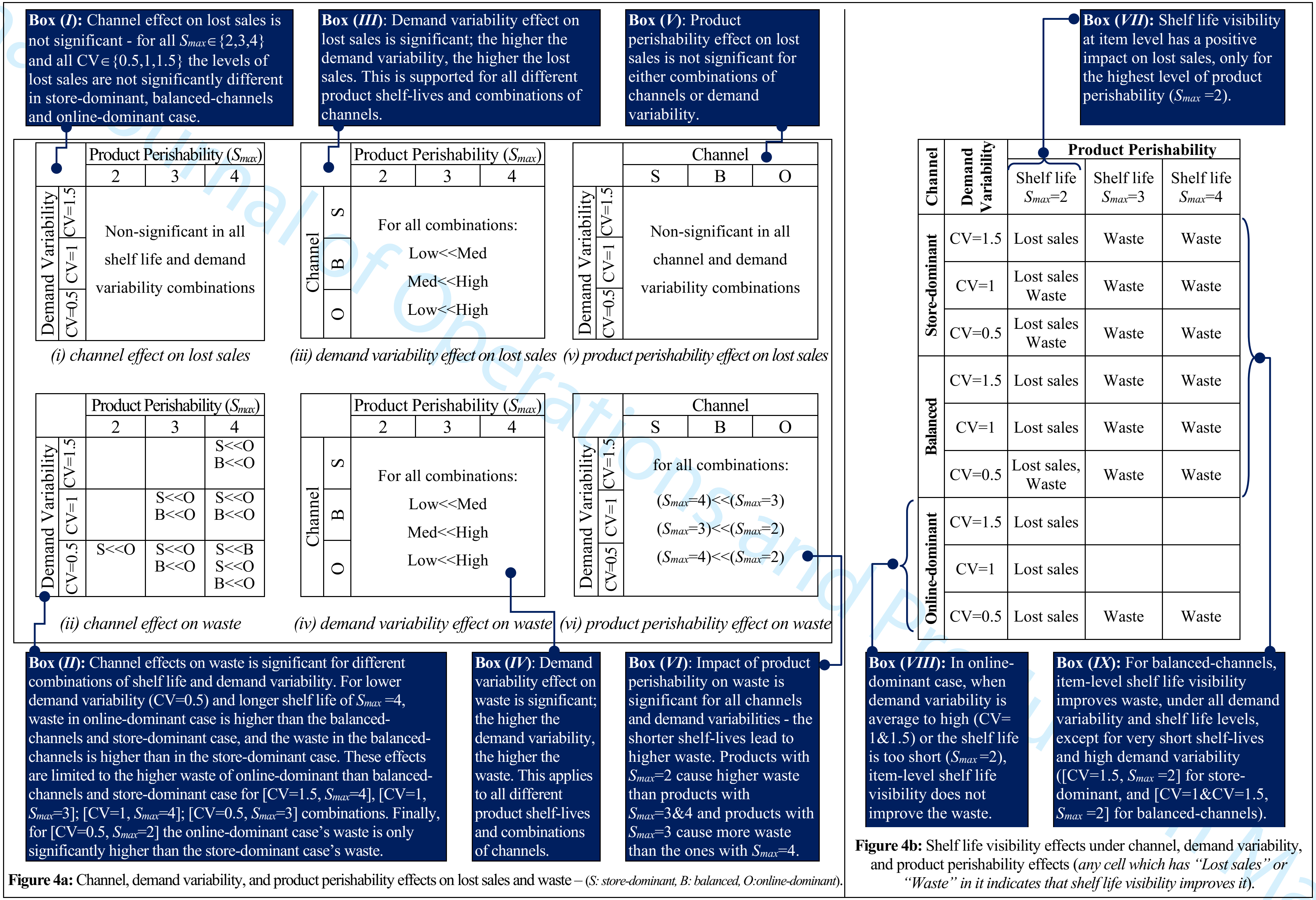

Figure 4a: Channel, demand variability, and product perishability effects on lost sales and waste – (*S: store-dominant, B: balanced, O:online-dominant*).

Figure 4b: Shelf life visibility effects under channel, demand variability, and product perishability effects (*any cell which has "Lost sales" or "Waste" in it indicates that shelf life visibility improves it*).

Figure 4. Influencing factors effects on waste and lost sales significance analysis (significant at α=0.05).

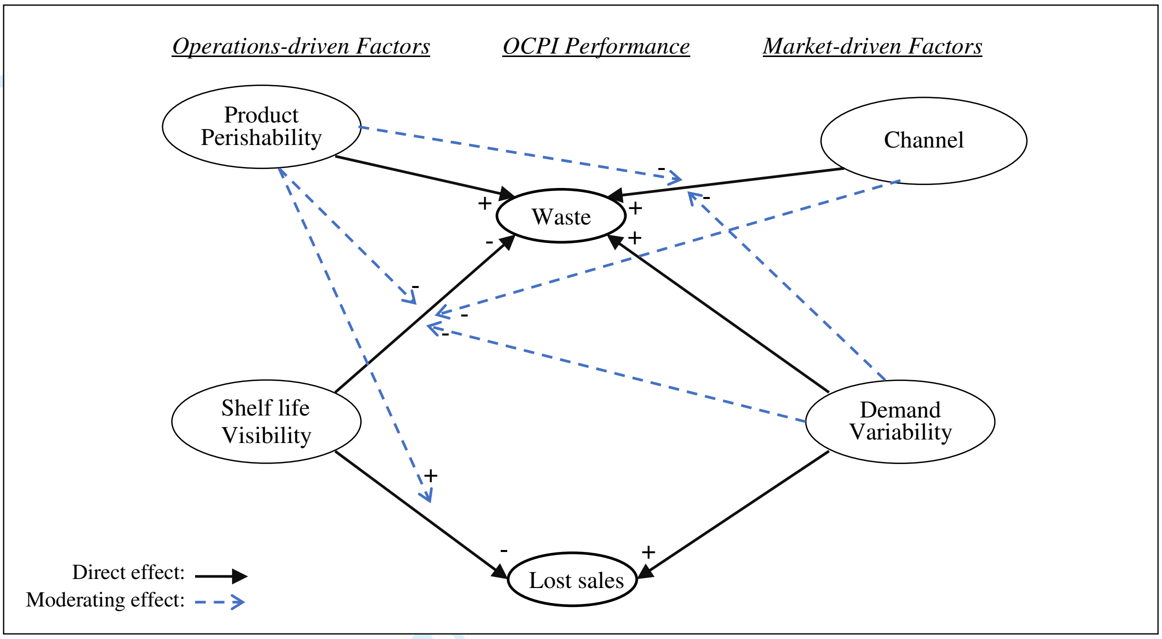

Figure 5. Direct and moderating effects on OCPI performance.

Supplementary File: Systematic Literature Review – Summary of Outcomes

Main Steps

Tasks	***Outcomes***
Initial literature review and scoping	Main keywords, core areas to focus on, and scope of the SLR
Search string definition	Two main search areas are defined: - Inventory - Perishability
Search string validation: - subject and library expert reviews - keyword amendments - search string finalization	Final search strings: - perish* OR deteriorate* OR decay* OR shelf-life OR "shelf life" OR life-time OR "life time") AND - inventor* OR stock* OR replenish* OR fulfil*
Database selection and confirmation - information specialist review	Search databases✦: - ABI/INFORM (ProQuest) - Business Source Complete (EBSCO) - SCOPUS
Search run in Title, Abstract, Keywords (or with equivalent filters)	- Initial Results: - ABI: 1072 - EBSCO: 116 - SCOPUS: 430
Initial Screening - Language (English) - Source Type (Journal Article) - Duplications removed	Total number of papers resulted: - 1019
Setting inclusion/exclusion criteria and further screening: - Subject area screening - Title and abstract screening	Total number of papers resulted: - 464
Full-text screening based on - Relevance - Quality	Total number of papers resulted: - 151
Snowballing - Relevant missing papers to be added	Final number of papers resulted: - 155

✦ Databases features:

Database	***Main Features***
ABI/Inform Complete (ProQuest)	Provides reports on various business disciplines by major commercial publishing houses. The database has a long backtracking period, and more than 60% of the journals have a backtracking time of more than 10 years.
EBSCO	Covers various subjects such as science, engineering, agriculture, medicine, business management, finance, literature, history and philosophy. There are more than 21,700 abstract journals, of which more than 6,800 journals can provide full text.
SCOPUS	Contains 19,000 source journals from 4,000 publishers around the world, and is the world's largest abstract and citation database, including scientific/technological literature.

Thematic Analysis Summary Outcomes

Product Shelf life

Type of Shelf life	***Reference***
Fixed shelf life	Abbasi and Hosseinifard (2014); Alvarez et al. (2020); Amorim et al. (2014); Avinadav and Arponen (2009); Avinadav et al. (2013); Avinadav et al. (2014); Balkhi and Benkherouf (2004); Berk and Gürler (2008); Berk et al. (2009); Berk et al. (2020); Broekmeulen & van Donselaar (2009); Buisman et al. (2019); Chang et al. (2016); Chen et al. (2016b); Chen et al. (2021); Chew et al. (2009); Chew et al. (2014); Chen et al. (2020); Chun (2003); Chung and Liao (2006); Chung and Wee (2011); Cooper (2001); Dasu and Tong (2010); Dey et al. (2008); Dobson et al. (2017); Ferguson et al. (2007); Ghiami and Beullens (2016); Ghiami et al. (2013); Haijema (2013); Haijema (2014); Haijema et al. (2007); Herbon (2014); Herbon (2015); Herbon (2016); Herbon (2021); Kanchanasuntorn and Techanitisawad (2006); Katagiri and Ishii (2002); Ketzenberg and Ferguson (2008); Kouki et al. (2015); Li et al. (2009); Li et al. (2012); Lian and Liu (2001); Lowalekar et al. (2016); Lodree and Uzochukwu (2008); Lu et al. (2020); Minner and Transchel (2010); Muriana (2016); Nandakumar and Morton (1993); Olsson (2014); Olsson and Tydesjö (2010); Pauls-Worm et al. (2016); Perry and Posner (1998); Shen et al. (2011); Ramanathan (2006); Suárez Díaz et al. (2020); Tsai and Huang (2012); Wang (2002); Wee and Widyadana (2012); Xu and Sarker (2003); Yan et al. (2013); Yang et al. (2019); Zanoni & Zavanella (2007)
Deteriorate with time	Al Hamadi et al. (2015); Blackburn and Scudder (2009); Buisman et al. (2019); Chang et al. (2010); Chung and Huang (2007); Chung and Liao (2004); Dye (2007); Dye and Ouyang (2005); Gallego et al. (2008); Kalpakam and Shanthi (2006); Kar et al. (2001); Kouki et al. (2014); Kouki et al. (2016); Lee (2006); Li et al. (2007); Liao, J.-J. (2008); Mahata (2012),; Mahata and Goswami, (2007); Molana et al. (2012); Niu and Xie (2008); Pal et al. (2006); Qin et al. (2014); Rau et al. (2003); Sicilia et al. (2014); Shah et al. (2005); Shi et al. (2021); Soni (2013) ; Teng and Yang (2004); Tsai and Huang (2012); Wee et al. (2009); Yang (2004); Yang (2006); Yang et al. (2010);
Age Dependent Deterioration	Chen and Lin (2002); Goh et al. (1993); Hsu (2000); Ketzenberg et al. (2015); Papachristos and Skouri (2003); Skouri et al. (2009); Jing and Mu (2020)
Inventory Dependent Deterioration	Bhattacharya (2005); Chung and Liao (2004); Hou (2006); Lee (2006); Zhang and Wang (2020)

Perishable products demand type

Demand type	***References***
Fixed/ uniform	Blackburn and Scudder (2009) Chung and Huang (2007) Ferguson et al. (2007) Hsu et al. (2010) Liao (2008) Mahata and Goswami, (2007) Nasr et al. (2014) Ouyang et al. (2005) Rau et al. (2003) Shah et al. (2005) Shen et al. (2011) Xu and Sarker (2003) Yang (2004) Yang and Wee (2003) Yang et al. (2019)
Probabilistic/ Stochastic/ Fuzzy	Abbasi and Hosseinifard (2014) Akçay et al. (2010) Al Hamadi et al. (2015) Barron (2019) Berk and Gürler (2008) Berman and Sapna (2002) Broekmeulen and van Donselaar (2009) Buisman et al. (2019) Chen et al. (2020) Chun (2003) Cooper (2001) Ferguson and Ketzenberg (2006) Ferguson and Koenigsberg (2007) Gallego et al. (2008) Gürler and Özkaya (2008) Haijema (2014) Herbon (2016) Kalpakam and Shanthi (2006) Katagiri and Ishii (2002) Ketzenberg and Ferguson (2008) Kouki et al. (2013) Li et al. (2014) Li et al. (2017) Lian and Liu (1999) Lowalekar et al. (2016) Mahata and Goswami (2007) Mallidis et al. (2020) Minner and Transchel (2010) Muriana (2016) Olsson (2014) Perry and Posner (1998) Tekin et al. (2001)
Stock- dependent	Agi and Soni (2020) Balkhi and Benkherouf (2004) Berk et al. (2020)

Demand type	*References*
	Bhattacharya (2005) Chang et al. (2010) Chen et al. (2016a) Chowdhury et al. (2014) Dye (2020) Dye and Ouyang (2005) Hanukov et al. (2021) Hou and Lin (2006) Kar et al. (2001) Pal et al. (2006) Qin et al. (2014) Wee et al. (2009) Wu et al. (2006) Yang (2014) Yang et al. (2010) Zhou and Yang (2003)
Price-Dependent	Abad (2003) Agi and Soni (2020) Avinadav et al. (2013) Berk et al. (2009) Bisi and Dada (2007) Chen and Chen (2005) Chew et al. (2009) Chintapalli (2015) Dasu and Tong (2010) Dye (2007) Dye (2020) Frank et al. (2009) Herbon (2014) Herbon (2021) Hou and Lin (2006) Li and Teng (2018) Li et al. (2009) Li et al. (2014) Lu et al. (2020) Lyi et al. (2012) Papachristos and Skouri (2003) Qin et al. (2014) Rong et al. (2008) Sezen (2004) Teng et al. (2007) Tsao and Sheen (2008) Wang et al. (2016) Wee and Law (2001) Zhang and Wang (2020)
Changing over time	Alvarez et al. (2020) Avinadav et al. (2013) Balkhi and Benkherouf (2004) Broekmeulen and van Donselaar (2009) Chen and Chen (2005) Chen and Lin (2002)

Demand type	***References***
	Chołodowicz and Orłowski (2021) Chung and Tsai (2001) Deng et al. (2007) Goyal and Giri (2003) Jing and Mu (2020) Kouki et al. (2013) Pauls-Worm et al. (2016) Shi et al. (2021) Sicilia et al. (2014) Skouri et al. (2009) Wang (2002) Wu (2001)
Freshness/Age Dependent	Agi and Soni (2020) Avinadav and Arponen (2009) Avinadav et al. (2014) Chen et al. (2016a) Chen et al. (2020) Deniz et al. (2020) Dobson et al. (2017) Dye (2020) Herbon (2014) Li and Teng (2018) Piramuthu and Zhou (2013) Qin et al. (2014) Suárez Díaz et al. (2020) Tsiros & Heilman (2005) Yang et al. (2020)

Inventory model objective (performance measures)

Objectives / Reference	Purchasing cost	Inventory holding	Ordering	Waste	Stock-out (backlog/lost sales)	Other
Abbasi and Hosseinifard (2014)				Cost of outdated items	Cost of shortage	
Al Hamadi et al. (2015)		Inventory holding cost	Ordering cost	Perishing cost		Customer waiting time
Ali et al. (2013)	Reducing purchase cost	Inventory holding cost	Ordering cost	Reducing deteriorating cost	Reducing shortage (in the form of backlog) cost	
Avinadav and Arponen (2009);		Inventory holding cost	Ordering cost			
Barron (2019)		Inventory holding cost	Ordering cost		Shortage cost	
Berk et al. (2020)		Inventory carrying cost	Ordering cost	Perishing cost	Lost sales	
Buisman et al. (2019)				Reducing waste	Reducing shortage	
Chen et al. (2016a)		Inventory holding cost	Ordering cost			Freshness (reflected in the price/ revenue); Shelf space cost
Chen et al. (2020)		Inventory holding cost	Ordering cost	Expiration cost	Shortage cost	
Chen et al. (2021)		Inventory holding cost	Ordering cost	Expiration cost, & disposal cost	Lost sales cost	
Dan and Liao (2013)				Reducing outdate rate		
Dobson et al. (2017)		Inventory holding cost	Replenishment cost			
Ferguson and Koenigsberg (2007)		Inventory holding cost		Expiration cost		

Objectives / Reference	*Purchasing cost*	*Inventory holding*	*Ordering*	*Waste*	*Stock-out (backlog/lost sales)*	*Other*
Haijema (2014)		Inventory holding cost		Waste cost; and Discounting/penalty costs for issuing old items that will expire at the end of the day	Shortage cost	
Haijema and Minner (2019)				Reducing waste	Reducing shortage	
Herbon (2021)		Inventory holding cost	Ordering cost	Expiration cost		
Hsu (2000)		Inventory carrying cost	Ordering cost			
Jing and Mu (2020)		Inventory holding cost	Reducing ordering cost			Substitution cost
Kalpakam and Shanthi (2006)	Purchase cost	Inventory holding cost	Ordering cost		Shortage cost	
Kendal and Lee (1980)		Holding down inventory carrying costs		keeping the amount of product spoilage (outdating) at an acceptable level		Keeping the cost of rotation low; Satisfying demand by carrying sufficient inventories; Maintaining quality by using the product while it is still fresh
Kouki et al. (2013)	Purchase cost	Inventory carrying cost	Ordering cost	Reducing outdate cost	Reducing backlog costs	
Li et al. (2009)		Inventory carrying cost	Ordering cost	Disposal cost	Backlog cost	
Li et al. (2012)	Purchase cost	Inventory holding cost	Ordering cost	Disposal cost	Cost of lost sales	
Lian and Liu (1999)		Inventory carrying cost	Ordering cost	Decaying cost	Shortage (backlog) cost	

Objectives / Reference	Purchasing cost	Inventory holding	Ordering	Waste	Stock-out (backlog/lost sales)	Other
Lowalekar et al. (2016)		Inventory holding cost	Ordering cost	Wastage cost	Shortage cost	Inventory review cost
Nandakumar and Morton, (1993)		Inventory holding cost	Ordering cost		Shortage penalty cost	
Nasr et al. (2014)		Inventory holding cost	Ordering cost			
Olsson (2014);		Inventory holding cost	Ordering cost	Perishing cost	Backorder cost; lost sales cost	
Qin et al. (2014)	Purchase cost	Inventory holding cost	Ordering cost	Disposal cost		
Shah et al. (2005)	Purchase cost	Inventory holding cost	Ordering cost	Deterioration cost		
Shi et al. (2021)	Purchase cost	Inventory holding cost	Ordering cost			Interest paid
Sicilia et al. (2014)	Purchase cost	Inventory holding cost	Ordering cost	Deteriorating cost	Shortage (backlog is permitted) cost	
Suárez Díaz et al. (2020)		Inventory holding cost	Ordering cost	Spoilage cost		
Yang et al. (2019)		Inventory holding cost	Ordering cost	Deterioration cost		Preservation costs
Zhang and Wang (2020)		Inventory holding cost	Ordering cost	Product decay cost		

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