A data-driven decision support system with smart packaging in grocery store supply chains during outbreaks

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A data-driven decision support system with smart packaging in grocery store supply chains during outbreaks

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ABSTRACT

The unexpected emergence of the COVID-19 pandemic has changed how grocery shopping is done. The grocery retail stores need to ensure hygiene, quality, and safety concerns in-store shopping by providing "no-touch" smart packaging solutions for agri-food products. The benefit of smart packaging is to inform consumers about the freshness level of a packaged product without having direct contact. This paper proposes a data-driven decision support system that uses smart packaging as a smart product-service system to manage the sustainable grocery store supply chain during outbreaks to prevent food waste. The proposed model dynamically updates the price of a packaged perishable product depending on freshness level while reducing food waste and the number of rejected customers and maximising profit by increasing the inventory turnover rate of grocery stores. The model was tested on a hypothetical but realistic case study of a single product. The results of this study showed that stock capacities, freshness discount rate, freshness period, and quantity discounts significantly affect the performance of a grocery store supply chain during outbreaks.

1. Introduction

The coronavirus pandemic continues unabated worldwide, affecting human society, including agriculture, manufacturing, and all service-providing industries [1,2]. In particular, grocery store supply chains were massively disrupted during the COVID-19 pandemic, resulting in short-term supply/demand imbalances (stockpile or stock out conditions) [3], delays in the replenishment of food shelves (empty and sparse shelves) [4], spoilage of perishables, increasing food waste [5–7] and growing consumers' concerns about food quality and safety [1]. In addition, the online retail boom triggered by the crisis has also created a significant disruption in shopping and consumption habits [8], especially among the consumers who had been in the practice of buying loose until now [9]. In recent years, scholars and practitioners have focused on food waste reduction in the retail sector [10]. Cicatiello et al. [11] state that food waste causes a global, nutritional and environmental problem, and it can emerge in all stages of the supply chain, with different features and reasons. The authors analyse the food waste records of a large retailer to detect edible food waste and unrecorded food waste. Lee & Tongarlak [12] investigate the retail stores' strategies to productively use waste as an input ingredient for a prepared food product. Moraes et al. [13] carry out a systematic literature review to determine the leading causes of food waste and the common practices applied to reduce or prevent food waste in the retail sector. Kazancoglu et al. [14] state that some food waste management policies cannot be enforced in emerging economies since the lack of efficient planning in recycling activities. The authors study the reasons for food waste faced by retailers. Schanes et al. [15] examine the existing literature review on consumer food waste and analyse the factors preventing or stimulating consumer food waste. Ekren et al. [16] attempt to minimise food waste by proposing a novel design for IoT-enabled sustainable food supply chain networks. According to a recent study on fifteen countries [17], fruits and vegetables significantly contribute to the total food waste where the total amount of fruit and vegetable food waste in Japan and

Abbreviations: smart PSS, Smart Product-Service Systems; RFID, Radio Frequency Identification; TTI, Time-Temperature Indicator; IoT, Internet of Things; ANOVA, Analysis of Variance.

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South Africa are 47.5 and 3.3 kg per person per year, respectively. According to a recent survey in Canada, 51.9% of household food waste is identified as fruit and vegetables during the COVID-19 pandemic [18]. Today, there is an increased demand for packaged products to meet customer needs [19,20] since packaging has been associated with safer, efficient, and cost-effective than loose-selling [21,22].

As nationwide lockdowns and restrictions set in, on-shelf availability of perishable food inventories may be disrupted, even leading to stockouts and waste [3,4]. During this challenging time, the grocery retail stores, on the one hand, need to ensure that they have a sustainable reserve of perishable food to meet the in-store market demand. On the other hand, they must overcome critical problems such as low hygiene, spoilage, and wastage due to the shorter shelf life of perishable loose products [8]. According to Ref. [15]; certain unexpected conditions cause people to stockpile and buy more than they can consume, which leads to food waste. For example, according to a recent survey of US households [23], consumers started to stockpile more food due to the increased risk of shortages during the COVID-19 pandemic, which also increased food waste. Furthermore, consumers waste 30% of food in the US and most rural areas of developing countries [24,25]. According to Damiani et al. [26], although the majority of the food waste is generated in the household, 5% of the food waste occurs in the retail and distribution stages. A significant amount of avoidable food waste is generated during the distribution stage. For example, an avoidable food waste of 27.1 kg per ton of fresh apple is generated during wholesale and retail processes of the supply chain [27]. The amounts of food waste are even more significant in wholesale and retail operations for bananas and potatoes (42.8 and 138.2 kg per ton, respectively). Changes in consumer preferences for safe food and efforts to reduce food waste have led to packaging technology innovations [28,29]. These challenges mentioned above lead to the digital transition and business innovations through digital servitisation [30–32], where Smart Product-Service Systems (smart PSS) provide capabilities to collect and transmit user-generated and sensed data among different stakeholders in an ecosystem while enabling real-time requirement-driven improvements [33]. As a smart PSS, smart packaging technology enables the packaging itself to send information to consumers and grocery retail stores [34] and supports retailers for smart reallocation/redistribution [33,35]. In particular, big retailers (e.g., Amazon) are launching new services (such as Amazon Dash Replenishment Service) with the implementation of smart packaging and devices with embedded technologies in their grocery retail stores (e.g., Amazon Go) to monitor the need for new supplies and enable automatic reordering experience.

The widespread use of food packaging today allows for higher quality and safe "no-touch" packaged products. Safe packaging practice is necessary for human health and safety hazards to prevent any pandemic from reducing the risk of infection. However, conventional ("non-smart") packaging systems do not provide any information about the quality and safety conditions of food to the consumers and manufacturers at any stage of the supply chain [36]. The utilization of smart packaging technologies offers contactless solutions for interaction with finished agri-food products to monitor and control food quality-related threats [37], track processes for inventory and life cycle management [38] and ensure higher automation throughout the food supply chain [19] while addressing quality and safety concerns of consumers amid outbreaks. Smart packaging systems can generate an advanced product using non-traditional packaging functions to provide safer, more reliable, and more nutritious or appealing food products while being environmentally friendly [21]. Smart packaging gives the product a digital identity with packaging features that communicate information such as shelf life, freshness, and quality, detection of damage, foreign materials or signs of spoilage (e.g., biochemical and microbial contamination) [29], and to track food safety involving food fraud (counterfeiting, theft, smuggling) [39,40]. Furthermore, this communication is becoming smarter with the integration of emerging technologies such as Radio Frequency Identification (RFID), QR-codes, near field communication, hyperspectral imagining, big data, Internet of Things (IoT), near-field communication (NFC), Time-Temperature Indicator (TTI), cloud services, and blockchain, in a variety of different combinations [2,34,39,41,42]. Through smart packaging, perishables can be monitored from A to B and kept in optimum conditions; and counterfeits can be sorted from genuine ones before they hit the shelves. As a result, the connected packages (boxes, pallets, and batches) are helping cut costs, inefficiencies, and mistakes within the food supply chain. Despite the high potential role of smart packaging in the food supply chain, the implementation of smart packaging in commercial applications is still limited [43]; moreover, there is no research conducted to show the potential implications of smart packaging application for perishable products in grocery store supply chain to maximise profits and reduce food waste. According to Ref. [44]; many retailers use price reduction strategies to sell perishable products near their best-before dates. Some retailers use technology to control temperature and train their staff to proactively decide stock rotation or price reductions for products with new best-before dates. However, very few of them use computer-assisted decision processes to order and make stocking decisions, but none of them is reported to be using dynamic price adjustments according to the actual situation of the products [44]. Therefore, there is a need to understand the potential of smart packaging to manage the grocery store supply chain during outbreaks to prevent food waste. In this study, the below research question is raised:

- What is the role of smart packaging as a smart PSS for perishable products in the sustainable grocery store supply chain to prevent food waste under unprecedented outbreaks?

This study fills this gap by developing a new data-driven decision support system to dynamically adjust the discount rate and make stocking and packaging decisions according to the actual freshness of the product to prevent food waste in a grocery retail store. The process of making decisions based on data analysis rather than intuition is known as data-driven decision making [45], and a data-driven decision support system generates good solutions for a problem using real-time data and helps the decision makers to make the correct decisions. Due to the complexity of the realistic and practical conditions posed by the COVID-19 pandemic, the proposed method herein uses a data-driven decision support system to find the best operational settings of a grocery retail store for perishable products. Smart labelling technology conveys complex information such as the country of origin, expiration date, and freshness level of produce. This is an essential technology aspect considering thousands of consumers have to choose from a huge number of different food products within a grocery store. The smart labelling technology can be programmed to dynamically update the price depending on the freshness level of produce, which will especially yield crucial results for packaged perishable produce. To the best of our knowledge, none of the papers in the literature investigates smart packaging systems in terms of dynamic price updates and produce freshness level perspective. The proposed model dynamically updates the price of the packaged perishable product depending on the freshness level displayed on the smart package label while reducing food waste in-store and the number of rejected customers and maximising profit by increasing the inventory turnover rate of a perishable product. Note that the cost of smart packages is not considered in this study, because it is assumed to be included in the price. The proposed methodology has been tested on a realistic but hypothetical case study of the packaged produce for apples. The results showed that stock capacities, freshness discount rate, freshness period, and quantity discounts are significant factors in improving grocery retail stores' performance to prevent food waste during the outbreaks.

The rest of the paper is organised as follows: Section 2 presents an overview of the related literature on dynamic pricing, smart packaging technology, the role of smart packaging system in the grocery store supply chain in outbreaks, and explains the contributions of this study. Section 3 introduces the proposed data-driven decision support system.

The model is tested on a realistic case study in Section 4. The results and discussion are given in Section 5. Finally, the paper is ended with the conclusion and future scope of work in Section 6.

2. Research background

As Frishammar et al. [46] stated that servitisation and digitalisation are two new trends in today's business environment. The companies have been transforming themselves into solution providers for PSS and combining physical products with smart components. In a recent literature review, Pirola et al. [47] pointed out that servitisation and digitalisation can help achieve smart PSS. Therefore, smart technologies can support smart services throughout their PSS lifecycles [48]. For example, blockchain technology can be used in PSS and improve the traceability of the product life cycle [49]. The products can be traced and tracked from the suppliers to the customer using blockchain technology in a retail supply chain [50]. It can also be beneficial to make the product life cycle information more visible and accessible. However, to achieve this, various smart products and sensor technologies must be used [51,52]. In addition [53], stated that Digital Twin could help monitor the product life cycle because it includes dynamic and static information. The Digital Twin can also help make smart decisions where "smart products" can decide their future. This concept is also crucial for perishable products, and it can also be applied to grocery store supply chains. Therefore, the relevant state-of-the-art literature on smart packaging and smart technologies in grocery store supply chains for perishable products during outbreaks is investigated in this section.

2.1. Smart packaging

Smart packaging, also called "intelligent packaging", refers to any form of packaging that can offer extra benefits to consumers and all associated food supply network partners [6]. These benefits include facilitating decision making, extending shelf life, prolonging food freshness, improving food safety, improving food quality, providing information, and warning about potential problems [2,54]. Yam et al. [55] defined a package as smart if it can carry out intelligent functions such as monitoring the product, perceiving and evaluating the interior and exterior atmosphere of the package, and communicating with the consumer. Smart packaging incorporates advanced and integrated sensing and communication technologies, e.g., moisture control and monitoring devices, detection sensors, IoT devices, RFID labels, to provide enhanced functionality (e.g., enabling automatic and dynamic pricing at the retail level) compared to traditional packaging [56,57]. According to Ghoshal [58], smart packaging can be classified into simple smart packaging and interactive or responsive smart packaging. The interactive type of smart packaging contains sensors and indicators to measure the status of packaged food. There are mainly three types of devices available for smart packaging: (i) external indicators: placed outside of the package to monitor environmental conditions for a time, temperature, and humidity to measure the effect of the kinetics of changes in food quality [59]. TTIs, integrity indicators, rancidity indicators, ripeness indicators, food spoilage indicators, gas leakage indicators, and humidity sensors belong to this type [43,60–65]. Furthermore, this gadget can also alert an interruption, e.g., incorrect freezing, heated above or cooled below a predefined temperature, on the cold chain and report when it has occurred and also records the complete history of the temperature/humidity profile along the supply chain [5]; (ii) internal indicators: attached inside of the package either on the bottom or under the lid of the package to track food quality-related compounds such as microbial growth or chemical changes against time within a food product [28]. Biosensors, freshness sensors, and indicators belong to this type [43]; (iii) data carriers: attached unique barcode/QR-code labels and RFID tags on the package to increase the efficient information flow and communication between product and consumer [7,43]. Data carriers provide store information about a food product, such as consumption procedure, storage condition, crop harvesting date, packing date, and best before the date and other product traceability, antitheft, anticounterfeiting, and tamperproof devices are also counted under this type [43,55]. These three types of indicators and sensors can also better monitor the quality level (freshness) of food products.

2.2. The role of a smart packaging system in perishable grocery store supply chain in outbreaks

The quality of agri-food products (agricultural fruits and vegetables) changes during their life cycle since they are perishable in nature [66]. The product characteristics and intrinsic quality attributes of these products are sensitive to various spoilage processes along the food supply chain [59]. Quality defects may arise from different mechanisms and depend on the type of food product, packaging, distribution, and storage conditions [43]. This can significantly affect the shelf life of the food product over the entire life cycle. In addition, the quality attributes of agri-food products can vary due to seasonality and local differences. According to a recent survey on young people by Burlea-Schiopoiu et al. [67], the COVID-19 pandemic has increased the awareness of food waste among young people and changed their consumption habits. The survey also revealed that young people have become more aware of food packaging solutions for the long-term preservation of food. However, overconsumption and overstocking have become a serious problem due to the insecurity related to the COVID-19 pandemic, especially during the first stage of the pandemic [67]. On the other hand, two recent surveys [68,69] during the lockdown in Italy showed that the consumers had reduced their food waste during the COVID-19 pandemic. Besides, today's consumers demand consistently high-quality food products that are safer, more affordable, less processed, and fresh, and the ongoing COVID-19 outbreak is accelerating this demand tremendously [2,70]. This complexity requires monitoring quality control, freshness, price, and waste of food products during the grocery logistics processes. Although consumers' perceptions towards packaging have not been researched adequately in the literature, Brennan et al. [71] stated that only a very small proportion (under 17%) of the consumers are aware of active and smart packaging solutions that can protect the products and prolong the shelf life. The use of smart packaging in the perishable grocery store supply chain has significant advantages [6], such as: improving the shelf life of inventory, reducing time and mistakes when reading stocks in store, monitoring the packaging conditions during in-store processes (e.g., no-touch freshness screening), preventing non-quality costs and reducing the cost of losses (food waste), reduced grocery store stockouts. Based on the information provided by such as TTI integrated smart packaging as to whether the actual remaining shelf life, in other words, the freshness of the perishable product is expected to be shorter than the expected ones, grocery retail stores can decide to reallocate products to discounters which can accept them at lower purchasing price [72]. In addition, grocery retail stores can also use a dynamic pricing strategy and decrease perishable products' unit selling price based on the dynamic expiry date [9]. Such discounts can increase the volume of products sold, reduce losses due to shrinkage and further reduce food waste [73]. In the literature, there is no data-driven decision support system for inventory or pricing decision developed with smart packaging for perishable products during outbreaks; only an inventory model was proposed for the drug supply chain with smart packaging application [74].

2.3. Grocery store operations for perishable products with smart technologies

In the grocery context, store operations experience new challenges and complexities. Product price and characteristics such as perishability/storability and package size can influence customers' behaviour in purchasing, replacing, and returning the product [75]. The out-of-stock situations have a detrimental effect on in-store customer retention. In addition, product degradation, along with the consumer's heterogeneous sensitivity to freshness, quality, and safety complicates inventory, assortment, shelf availability, and allocation decisions [75], and food waste also becomes a more significant challenge for store operations [9,76,77]. Setting the dynamic pricing models and replenishment policies based on real-time quality/freshness evaluation of perishable food by smart applications can potentially combat these challenges mentioned above [73,78]. Despite various studies in the literature, limited research has been conducted on store operation issues in the grocery supply chain addressing these challenges with dynamic pricing and smart technology integrations for perishable products [9]. Liu et al. [79] developed a dynamic pricing model for retailers to maximise the profit from selling perishable products with real-time information on product quality with RFID technology. Wang and Li [80] introduced a pricing strategy model based on dynamically identified food shelf life through tracking and tracing technologies such as RFID and TTI to reduce food waste and maximise the retailer's profit. Herbon et al. [81] considered the inventory management problem of perishable products with dynamic pricing using RFID-supported TTI-based automatic devices. In the model, consumption depends on the product's price and freshness. Li & Wang [82] explored the potential benefits of sensor data-driven pricing decisions on chilled food chain management and quantitatively analysed the effects of dynamic pricing strategy to reduce food waste. In a recent study, Aytaç & Korçak [83] proposed an edge computing-based system to use real-time sensor information (temperature, humidity weight) and other service-related data to monitor the actual status of the food and make better future decisions to reduce food waste in the restaurant industry. The pilot implementation of the proposed system in two restaurants yielded a 10% reduction in food waste.

With the increased amount of data generated by smart technologies, the importance of the use of data-driven decision support systems has improved. As summarized by Provost & Fawcett [45], companies can significantly improve their productivity, asset utilization profits, and market values with the use of data-driven decision-making practices. According to Power [84], a data-driven decision support system should link to a variety of data sources, be easy to use and understand, allow data manipulation, create flexible reports, and have strong analytical capabilities. Awan et al. [85] surveyed 109 companies from the Czech Republic and summarized that data-driven decision-making helps companies to make better and more effective decisions; however, strong big data analytics capabilities are required to fully utilize the benefits of data-driven decisions. In a fresh food supply chain application, Huber et al. [86] developed a decision support system to manage daily operations of perishable product supply chains by making accurate demand forecasts. However, they did not use the real-time IoT-based data as we proposed in this study. As summarized in Abideen et al. [87], a decision support system should combine IoT connectivity and real-time data to solve problems in Logistics 4.0 systems.

2.4. Dynamic pricing of perishable products

Dye [88] used dynamic programming to model the impacts of pricing, psychic stock, and freshness index of the product but also included advertising and ordering decisions. Feng [89] developed an optimal control model to find the optimal replenishment policy with dynamic pricing and quality investment for perishable products where product quality and physical quantity diminish over time. Buisman et al. [90] developed a shelf life modelling based on the predicted growth of the bacteria population in the meat products and discounted the meat price dynamically using simulation to reduce waste and increase profit. However, their model only considered microbiological modelling to estimate the Microbiological count of bacteria in the product and did not use the real-time data as suggested herein. Similarly, Chen et al. [91] also developed a model to dynamically adjust the menu prices of deteriorating fruit and vegetable products considering the decay rate. They also used the customer utility function to model buying decisions and compared one-time price changes and dynamic price adjustment strategies. Chernonog (2019), Das et al. [92], Huang et al. [93], and Tiwari et al. [94] proposed an inventory modelling approach for dynamic pricing of deteriorating products in multi-echelon supply chains using a game-theoretic approach. In recent studies, Kayikci et al. [9] proposed a data-driven multi-stage dynamic programming approach to decide on a pricing strategy for bulk produce, where real-time IoT sensor data is retrieved to analyse and determine the length of freshness scores. Keskin et al. [95] developed data-driven pricing and ordering policies for perishable products in grocery stores, including dynamic pricing and inventory management decisions to maximise profit.

This study addresses several gaps in the literature. First, none of the existing studies considered smart packaging technologies that monitor the actual quality status of products or the effect of predetermined package sizes on customer decisions. Second, this study considers three objective functions: (i) profit, (ii) daily total food waste, and (iii) daily rejected customers. Also, this study offers some important insights into identifying the most significant factors (stock capacities, freshness discount rate, freshness period, and quantity discounts) affecting the perishable grocery store supply chain performance and the interrelationships among these factors. Lastly, none of the studies in the literature considered the effects of the COVID-19 pandemic on dynamic pricing and retail supply chain operations. Thus, this study seeks to develop a novel methodology that helps to address these research gaps.

3. The proposed methodology

In this paper, a data-driven decision support system is proposed to investigate the effectiveness of smart packaging technology for perishable fresh produce such as fruits and vegetables. Innovative packing technology can enhance the traceability of in-store operations. The development of smart PSS offers a promising solution for grocery operations in terms of pro-environmental outcomes. Data-driven decision support systems enable grocery retail stores to tackle the challenges of carrying perishable foods during unpredictable sales seasons caused by unforeseen consequences of lockdowns. Smart packaging can detect the condition of the fresh produce and transmit this information to the store's computing systems. A data-driven decision support system is investigated under a four-stage setting in which the fresh produce decay in ten days. The freshness is measured by the sensors attached to each smart package, and this data is used to determine the dynamic price of the fresh produce at each stage of the proposed model.

The data-driven decision support system is demonstrated below in Fig. 1. The smart package has three colour indicators: green, yellow, and red. As the produce losses its freshness, the colour of the smart label changes. The green colour indicates the freshest stage of the produce, and the yellow colour shows slightly less freshness stage, the produce is still in good condition, and the red colour indicates poor freshness stage, the produce needs to be consumed in few days. As the smart label turns to different colours, the price of the produce changes dynamically and informs the buyers about the freshness level of the packaged product. The smart labelling system process during the life cycle of fresh produce is shown in Fig. 1.

As the produce becomes stale, the smart label's changing colours indicate that its "best by" date closes to the end. The system dynamically updates the price based on the freshness level indicated by the smart label colour. If an item is unsold at the end of the selling period, the smart label dissolves and does not reflect its freshness, and finally, the package is disposed of with the cost of the unit penalty. This is an unexpected situation for the firm; hence, a smart packing system's dynamic pricing strategy is beneficial for depleting the stock before the disposal stage. The sales process of this perishable produce is simulated where the price is being dynamically updated based on the colour represented on the smart label.

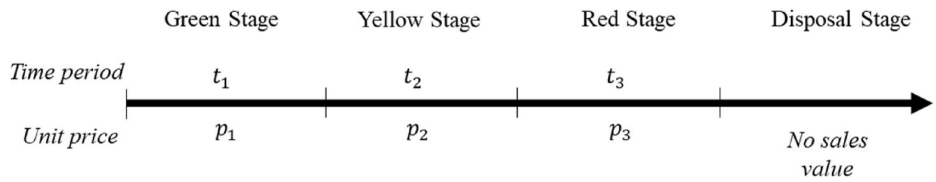


Fig. 1. Smart labelling timeline process.

Inventory replenishment of the grocery retail store is done daily from the main distribution centres, and the shelves are fed from the store's backroom throughout the day. The product is stored in bulk or loose in backrooms and packaged in predetermined package sizes. As a shelf becomes empty, it is filled with the different sized packages taken from the stockroom. A simple illustration of the grocery retail store is presented in Fig. 2.

The role of the smart packaging system for perishable products is significant during the outbreaks due to the COVID-19 pandemic. Unexpected lockdowns might impose profit loss associated with the high-volume waste. The smart packaging system ensures hygiene by nature and assists retail grocery retail stores with pricing strategies. The proposed data-driven decision support system explores the effects of these outbreaks on retail stores and how a smart packaging system mitigates the risk of high-volume waste. The consumer demand depends on the priorities: price, quality, package size, and freshness level, as well as lockdown conditions. The flow chart of the proposed model is given in Fig. 3.

The proposed data-driven decision support system imitates the 30-days sales period of a retailer. The customer types are set based on the priority attributes (e.g., quantity, quality, and price) at the beginning. The model decides lockdowns in a sales period based on the defined rule. When a lockdown emerges, the retailer experiences a dramatic increase in demand on that Friday. The following weekend after a lockdown has no sales; hence the rise in customer demand helps the retailer deplete its inventory before a lockdown and avoid the fresh produce decay resulting in waste. If a customer's priority and existing inventory match, the sale is realised and recorded. As time goes by, the colour code on the smart label changes and informs the consumers about the freshness stage of the produce. After the red colour, the produce is not saleable and must be disposed. The cost of smart packaging is assumed to be negligible in this study.

4. Case study

4.1. Experimental factors

This study aims to determine the best settings for maximising the daily profit and minimising total daily waste and daily rejected customers of grocery store supply chains. Therefore, to show the applicability and effectiveness of the proposed data-driven decision support system, apple produce is considered in this case study. The apples are packaged into two, four, or six units. The cost of smart packaging is not considered as a parameter in the simulation study, because it is assumed to be included in the price. Note that these smart packages closely monitor the freshness of the contents of the packages, and the price is determined dynamically, as explained in Section 3. In addition to daily profit, two other essential performance metrics (i.e., total daily waste and daily rejected customers) are minimised herein. Several factors regarding operational decisions of grocery retail stores during the COVID-19 pandemic affect these performance metrics.

Table 1 summarises the experimental factors considered in this study and corresponding their levels in the experimental design. The definitions of the factors used in this study are given below.

- *Stock Capacities:* The store designates three shelves for each type of package size. These shelves are filled with the product and continuously fed from the backroom, where the daily replenishment is held. Therefore, (100, 100, 100) denotes that each 2-pack, 4-pack, and 6-pack product has a stock capacity of 100.
- *Freshness Discount Rate:* As the smart label changes colour (green, yellow, and red), the price of the package is dynamically reduced.
- *Freshness Period:* Each colour on the smart label represents a different freshness period of the produce. For example, (5, 8, 10) represents the product has a green label for the first five days, then the label will stay as yellow for the next three days, and lastly, the label stays red for the last two days.
- *Quantity Discounts:* As the size of the package gets bigger, the unit price of the product becomes cheaper. For example, (5%, 10%) denotes 5% and 10% price discounts on 4-pack and 6-pack products, respectively.

4.2. Experiment and analyses

A four-factor factorial experimental design with three levels was employed to test the effects of various operational factors on the performance of grocery retail stores during the COVID-19 pandemic. A total of 3^4 (four factors with three levels) $x10$ (number of replications) = 810 test instances were simulated using Python 3.8. The duration of a simulation is 30 days. The effect of the COVID-19 pandemic is demon-

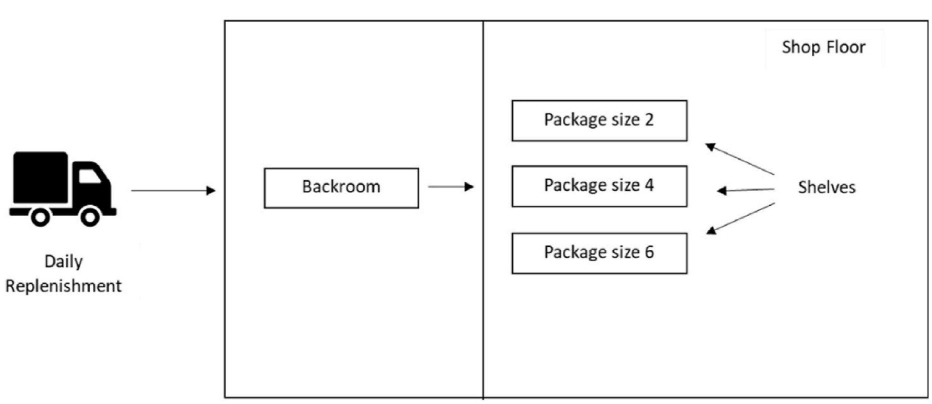


Fig. 2. Layout of the grocery retail store.

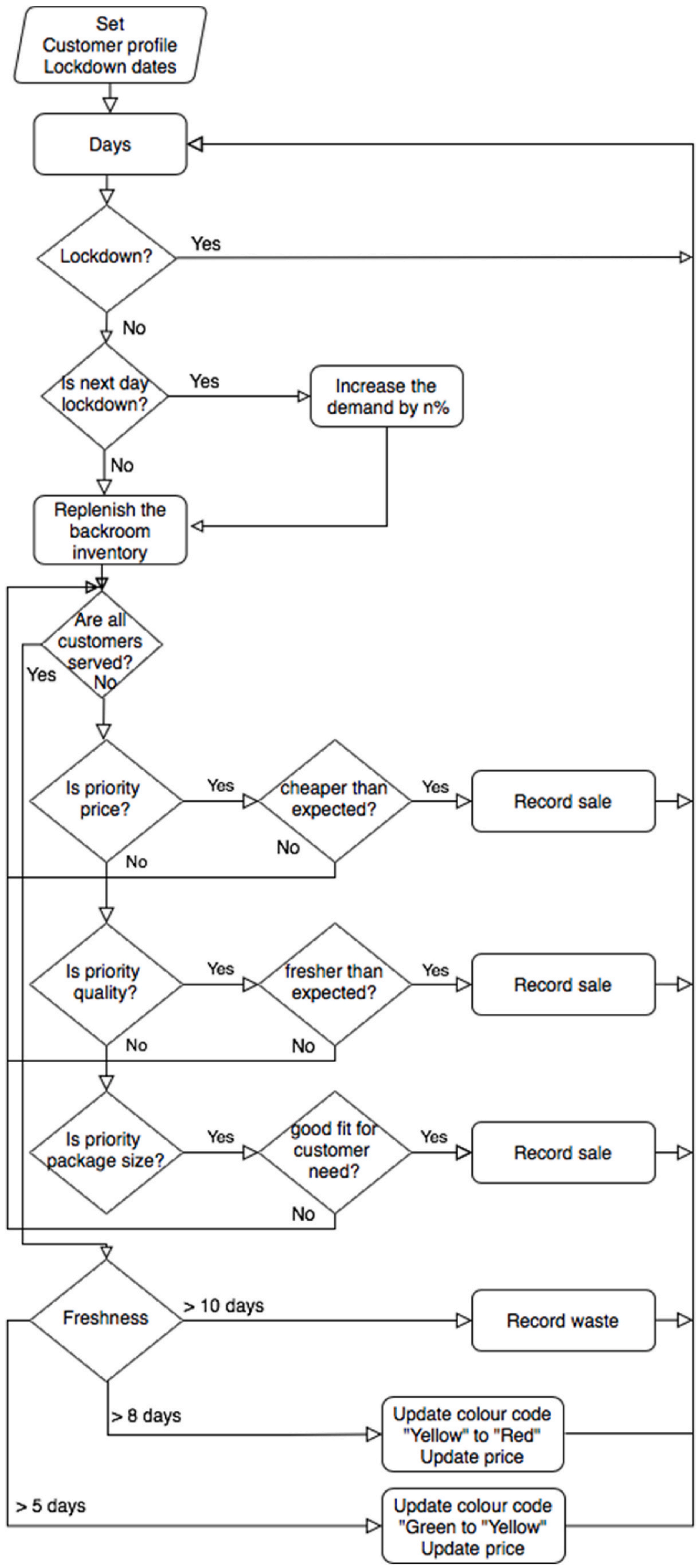


Fig. 3. The flow chart of the proposed model.

Table 1
The factors of the experimental design and their levels.

Factor		Factor Levels Level 1	Level 2	Level 3
A	Stock Capacities	(100,100,100)	(125,125,125)	(150,150,150)
B	Freshness Discount Rate	10%	20%	30%
C	Freshness Periods	(5,8,10)	(4,8,10)	(5,7,10)
D	Quantity Discounts	No Discount	(5%, 10%)	(10%, 15%)

strated by the unexpected lockdowns, as explained in Section 3. Only a single product is considered, and the inventory is assumed to be replenished daily. The daily number of customers is generated according to a normal distribution with a mean of 300 and a standard deviation of 50. Three priority attributes are defined, namely, (i) price, (ii) freshness, and (iii) package size, to present the customers' preference for their buying behaviour. Each customer's priority attribute is randomly assigned with one of these attributes. If the customer's priority attribute is assigned as price, the customer's maximum willingness (regardless of freshness and package size) to pay is randomly generated according to a normal distribution with the mean of the initial price and standard deviation of 15% initial price. If the customer's priority attribute is freshness, the customer's minimum freshness level (regardless of price and package size) to buy is randomly determined as one of the freshness levels (green, yellow, or red package labels).

Similarly, one of the package sizes (2-pack, 4-pack, or 6-pack) is randomly assigned if the customer's priority attribute is determined as package size. In that case, customers only buy their predetermined package size (regardless of price and freshness). According to the sales period, freshness levels are changed, as explained in Fig. 3. If the packaged product is unsold within ten days in the grocery retail store, it goes directly to waste. Note that the main goal of this study is to prevent food waste.

The results of the designed experiment were analysed using Analysis of Variance (ANOVA), where the level of significance is selected as 0.05. Considering the average daily profit performance metric, the significant main factors are stock capacities, freshness periods, and quantity discounts. Table 2 presents the p-values of the factorial fit ANOVA table for this experiment. According to the ANOVA analysis, none of the interactions is significant.

Table 2
Analysis of variance p-values for average daily profit ($) response.

Source	P-Value
Main Effects	0.000
Stock Capacities	**0.002**
Freshness Discount Rate	0.606
Freshness Periods	**0.000**
Quantity Discounts	**0.000**
2-Way Interactions	0.614
Stock Capacities*Freshness Discount Rate	0.690
Stock Capacities*Freshness Periods	0.722
Stock Capacities*Quantity Discounts	0.130
Freshness Discount Rate*Freshness Periods	0.227
Freshness Discount Rate*Quantity Discounts	0.976
Freshness Periods*Quantity Discounts	0.433
3-Way Interactions	0.380
Stock Capacities*Freshness Discount Rate*Freshness Periods	0.235
Stock Capacities*Freshness Discount Rate*Quantity Discounts	0.492
Stock Capacities*Freshness Periods*Quantity Discounts	0.381
Freshness Discount Rate*Freshness Periods*Quantity Discounts	0.494
4-Way Interactions	0.800
Stock Capacities*Freshness Discount Rate*Freshness Periods*Quantity Discounts	0.800

Fig. 4 shows the effects of the main factors. According to these results, the stock capacities of 100 units for 2-pack, 4-pack, and 6-pack products yield the maximum daily profit. In terms of freshness periods, five days for green labels and three days for yellow labels results in a higher daily profit. As determined from Fig. 4, no discount strategy for 4-pack and 6-pack products yields the maximum profit.

Average daily total waste is affected significantly by the main effects of stock capacities, freshness periods, and quantity discounts, as seen in Table 3. As presented in Fig. 5, similar to the average daily profit response, stock capacities of 100 units of 2-pack, 4-pack, and 6-pack products significantly reduce the average daily total waste value. Freshness periods of (5, 8, 10) improve the average daily total waste response. In contrast to the average daily profit response, quantity discounts of 5% for 4-pack and 10% for 6-pack products are required to reduce average daily total waste.

Considering the average daily rejected customers response, none of the main factors is statistically significant, as given in Table 4. However, the two-way interaction of stock capacities and quantity discounts is significant. The interaction between freshness discount rate and quantity discounts also has a large effect on the model. Fig. 6 shows the effects of these interactions on the average daily rejected customers. Stock capacities of 125 for all pack sizes minimise the daily rejected customers. Also, to minimise the number of rejected customers, the quantity discounts of 4-pack and 6-pack should be increased to 10% and 15%, respectively. Lastly, the discount rate between green, yellow and red freshness labels must be 20% to minimise the average percentage of rejected customers.

5. Result and discussion

By means of the proposed methodology, the efficiency of a grocery store supply chain can be increased during the erratic demand conditions of the COVID-19 pandemic. According to the results of the case study, the proposed methodology can help increase average daily profit and reduce both the average daily total food waste and the average percentage of daily rejected customers. The summary of the best factor level combinations of each performance metric is given in Table 5.

The simulation study revealed that the average daily profit is maximised, and total daily food waste is minimised by reducing the depot size of all packages because this minimises the food waste of the perishable products. Stock capacities of 100 for all products yield 2.17% more profit than those of 150; however, the difference between stock capacities 100 and 125 is negligible (0.24%). Choosing the freshness periods of (5, 8, 10) yields 0.75% and 4.76% more profit than choosing (5, 7, 10) and (4, 8, 10), respectively. No discount strategy increases the profits by 8.18% and 14.67% compared to (5%, 10%) and (10%, 15%) discount strategies, respectively.

In terms of average daily food waste, stock capacities of 100 for all package types yield 31.37% and 48.04% lower food waste amounts than those of 125 and 150. Although the difference in the average daily total food waste between freshness periods of (5, 7, 10) and (4,8,10) is large (−7.07%), the difference between (5, 7, 10) and (5, 8, 10) is negligible (−0.58%). On the other hand, changing the discount strategy from no discount to 5% for 4-pack and 10% for 6-pack reduces the average daily food waste by 1.13%.

Considering the average percentage of daily rejected customers, the depot capacity of 125 for all package sizes and a larger discount strategy (10%, 15%) significantly reduced the average number of rejected customers. Stock capacities of 100 and 150 significantly increase the daily rejected customers (4.51% and 15.63%, respectively) when compared to 125 customers at the same discount strategy (10%, 15%). However, the depot capacity of 100 and a lower discount strategy (5%,10%) increases customer rejection percentage by only 1.82%. Although the effect of the freshness discount rate is smaller with the discount strategy (5%, 10%), the freshness discount of 20% with the discount strategy (10%,15%) yields the lowest average customer rejection percentage, which is 2.81%

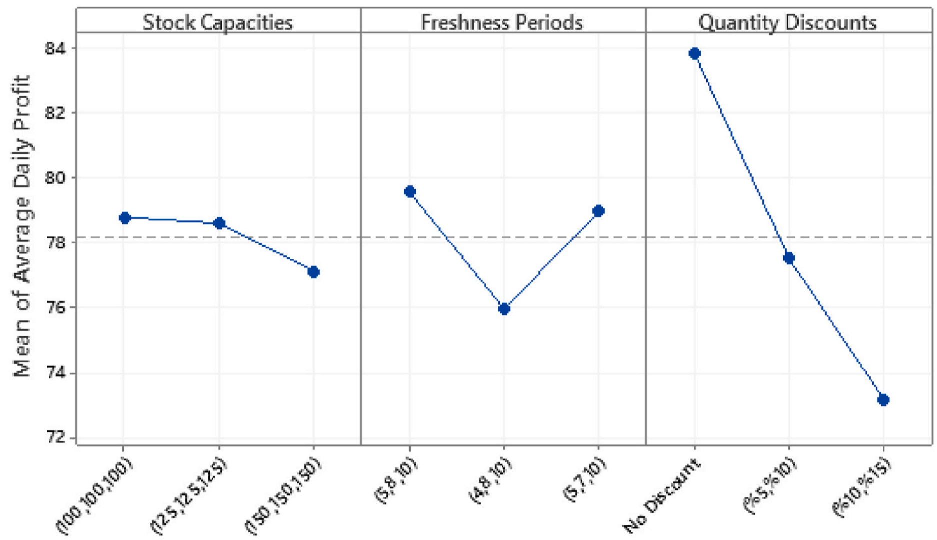


Fig. 4. Significant main effects for average daily profit ($) response.

Table 3
Analysis of variance p-values for average daily total waste response.

Source	P-Value
Main Effects	0.000
Stock Capacities	**0.000**
Freshness Discount Rate	0.733
Freshness Periods	**0.000**
Quantity Discounts	**0.017**
2-Way Interactions	0.614
Stock Capacities*Freshness Discount Rate	0.284
Stock Capacities*Freshness Periods	0.401
Stock Capacities*Quantity Discounts	0.489
Freshness Discount Rate*Freshness Periods	0.183
Freshness Discount Rate*Quantity Discounts	0.784
Freshness Periods*Quantity Discounts	0.922
3-Way Interactions	0.520
Stock Capacities*Freshness Discount Rate*Freshness Periods	0.230
Stock Capacities*Freshness Discount Rate*Quantity Discounts	0.716
Stock Capacities*Freshness Periods*Quantity Discounts	0.369
Freshness Discount Rate*Freshness Periods*Quantity Discounts	0.612
4-Way Interactions	0.126
Stock Capacities*Freshness Discount Rate*Freshness Periods*Quantity Discounts	0.126

and 13% less than the ones obtained by the freshness discount rates of 10% and 30%, respectively.

Finally, the proposed data-driven decision support system using smart packaging was compared with the existing sales strategy by executing ten simulation runs over a 30-day period. The results show that the smart packaging system yields a significantly higher profit and lower food waste than the current system. On average, smart packaging increases profit by 77% and reduces waste by 27%, as depicted in Fig. 7.

6. Conclusion

Smart PSS has gained significant attention from both practitioners and academics since the emergence of the digital technologies of Industry 4.0. Two important PSS trends, digitalisation and servitisation, can help businesses better assess the lifecycle of their products and effectively design and manage their supply chains. This concept has become even more important for perishable product supply chains as customers' shopping behaviour has changed dramatically since the emergence of COVID-19. No-touch (or touch-free, touchless) store experience is now becoming the new normal. Smart packaging systems offer customers a walk-in store experience and purchase fresh produce without the sense of touch. Besides, smart packaging systems help retailers collect more data and understand the customers' shopping behaviour. The more a store knows about its customers, the better it can meet their expectations and improve the shopping experience. Especially retail giants (e.g., Amazon) support smart packaging and devices with embedded technology that senses the need for new supplies, helping consumers automatically reorder products before they run out and access safe and healthy products. Therefore, smart packaging is becoming more and more prevalent to enable healthier, safer, and more connected lives.

A data-driven decision support system was conducted in this study to determine the best operational factors for grocery store supply chains during the COVID-19 pandemic. The proposed model addresses realistic and challenging characteristics of perishable food supply chains and the unprecedented conditions of the COVID-19 pandemic. The erratic demand of the pandemic and random lockdown rules have created challenges for grocery retail stores to increase their profits and reduce food waste of the perishable products. The key lesson learned from this study was that the grocery retail store using smart packaging may have the greater potential than the traditional grocery retail store to maximise profit and minimise food waste during outbreaks.

There are several theoretical and managerial implications of this study. As a theoretical contribution, this study is the first to propose a data-driven decision support system to analyse the operational settings of grocery retail stores for perishable products during the pandemic. Also, this model incorporates smart packaging that can monitor the freshness level of packaged products and food safety into the model to capture the realistic characteristics of perishable foods in grocery retail stores. Four factors (stock capacities, freshness discount rate, freshness period, and quantity discounts) were considered, and their effects on profit, food waste, and customer rejection were analysed. The proposed data-driven decision support system is implemented in a realistic case study.

From the managerial perspective, the managers can determine the best operational setting for the perishable products of their grocery store supply chains using the proposed methodology. This can be done for all perishable products sold within a store, and different factor levels can be determined to improve the bottom-line dollar figure and the other performance metrics. Another practical implication of this study is that the case study results have presented that the most important profit and food waste factors are stock capacities, freshness, and quantity discounts. Smaller stock sizes should be selected to maximise profit and

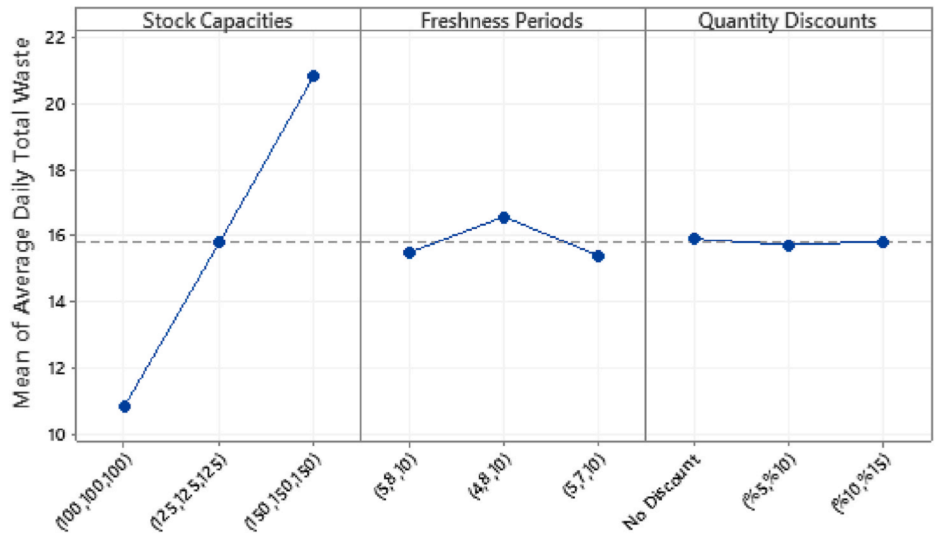


Fig. 5. Significant main effects for average daily total waste response.

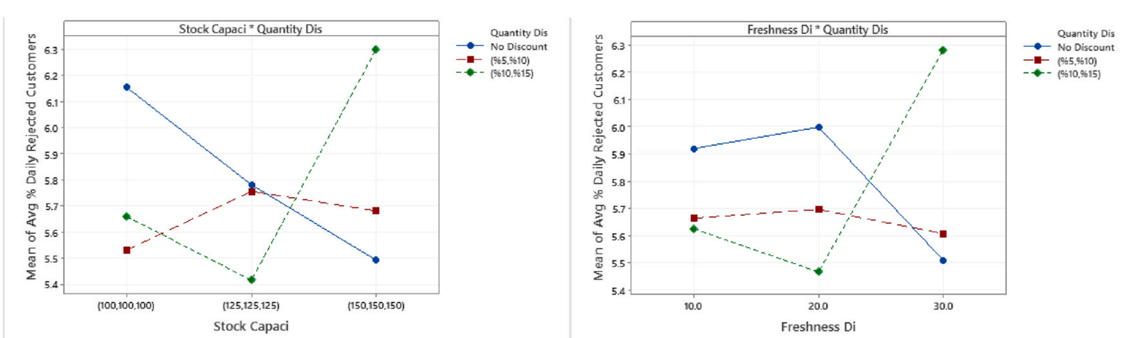
Table 4
Analysis of variance p-values for avg. percentage of daily rejected customer response.

Source	P-Value
Main Effects	0.564
Stock Capacities	0.635
Freshness Discount Rate	0.906
Freshness Periods	0.089
Quantity Discounts	0.677
2-Way Interactions	0.042
Stock Capacities*Freshness Discount Rate	0.103
Stock Capacities*Freshness Periods	0.805
Stock Capacities*Quantity Discounts	**0.024**
Freshness Discount Rate*Freshness Periods	0.222
Freshness Discount Rate*Quantity Discounts	**0.054**
Freshness Periods*Quantity Discounts	0.778
3-Way Interactions	0.515
Stock Capacities*Freshness Discount Rate*Freshness Periods	0.458
Stock Capacities*Freshness Discount Rate*Quantity Discounts	0.866
Stock Capacities*Freshness Periods*Quantity Discounts	0.438
Freshness Discount Rate*Freshness Periods*Quantity Discounts	0.181
4-Way Interactions	0.331
Stock Capacities*Freshness Discount Rate*Freshness Periods*Quantity Discounts	0.331

minimise food waste. However, this causes a significant increase in the number of rejected customers due to the erratic demand conditions of the COVID-19 pandemic. As for the freshness period, a longer green label period produces higher profit and lower food waste where it does not have a meaningful effect on the number of rejected customers. Although the discount rate between the freshness labels (green, yellow, and red) is not significant for-profit and food waste performance metrics, it should be set to 20% to reduce the number of rejected customers. Quantity discounts should be offered to reduce food waste and customer rejection rates; however, no discount strategy is suggested to maximise the profit during the pandemic. Note that this model can be simplified by removing the freshness factors (i.e., freshness discount rate, freshness period) and applied to regular retail stores to maximise profits and minimise customer rejection rates. The use of smart labelling technology

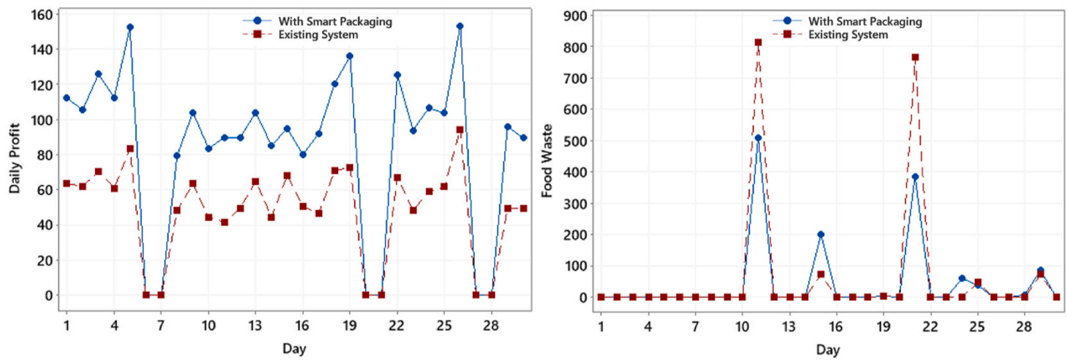
Table 5
Summary of the results.

Factors	Performance Metrics		
	Average Daily Profit	Average Daily Total Food Waste	Average Percentage of Daily Rejected Customers
Stock Capacities	(100, 100, 100)	(100, 100, 100)	(125, 125, 125)
Freshness Discount Rate	-	-	20%
Freshness Periods	(5, 8, 10)	(5, 7, 10)	-
Quantity Discounts	No discount	(5%, 10%)	(10%, 15%)



*a) Stock Capacities*Quantity Discounts* *b) Freshness Discounts*Quantity Discounts*

Fig. 6. Significant interaction effects for avg. percentage of daily rejected customers response.



a) Profit *b) Food Waste*

Fig. 7. The effect of smart packaging system on profit and waste.

for perishable products helps managers to track and measure the safety of perishable foods. The benefit of this technology is three-fold. First, smart labelling technology enables groceries to track food temperatures and freshness levels while increasing product sustainability and reducing waste. Second, this technology can dynamically update the product price depending on freshness. Lastly, it stores and conveys critical information such as country of origin, expiration date, and freshness level, ensuring customer satisfaction.

As a limitation of this study, the simulation analysis was performed using the Monte-Carlo simulation. In future studies, discrete-event simulation can be used to dynamically change the pricing strategies within the day to further increase profit and reduce both food waste and customer rejection rate. Furthermore, different replenishment strategies and multiple product types can be analysed to improve performance metrics. As another future direction, machine learning methods can be applied to dynamically allocate stock capacities and prices to different product types by examining the past demand data and local conditions. In addition, the implementation of the dynamic pricing method, especially in small grocery markets is more difficult because the proposed method requires expertise. Therefore, the applicability of this study in real-life is another limitation. Finally, this study assumes that the cost of smart packaging is included in the price; however, this assumption can be considered separately in future studies.

CRediT author statement

Ozgur Kabadurmus: Formal analysis, Investigation, Writing-Reviewing and Editing, Visualisation, Validation Yasanur Kayikci: Conceptualization, Supervision, Formal analysis, Methodology, Writing – original draft preparation, Writing- Reviewing and Editing Sercan Demir: Methodology, Data curation, Investigation, Visualisation, Validation, Writing – original draft preparation Basar Koc: Methodology, Data curation, Investigation, Validation, Software, Resources

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References

[1] Zurayk R. Pandemic and food security: a view from the Global South. J Agricult Food Syst Commun Dev 2020;9(3):17–21. https://doi.org/10.5304/jafscd.2020.093.014.
[2] Ma NL, Peng W, Soon CF, , H., M.F.N., Misbah S, Rahmat Z, Yong WTL, Sonne C. Covid-19 pandemic in the lens of food safety and security. Environ Res 2021;193. https://doi.org/10.1016/j.envres.2020.110405.
[3] Pu M, Zhong Y. Rising concerns over agricultural production as COVID-19 spreads: lessons from China. Global Food Secur 2020;26:100409. https://doi.org/10.1016/j.gfs.2020.100409.
[4] Galanakis CM. The food systems in the era of the coronavirus (COVID-19) pandemic crisis. Foods 2020;9(4):523. https://doi.org/10.3390/foods9040523.
[5] Müller P, Schmid M. Intelligent packaging in the food sector: a brief overview. Foods 2019;8(1):16. https://doi.org/10.3390/foods8010016.
[6] Liegeard J, Manning L. Use of intelligent applications to reduce household food waste. Crit Rev Food Sci Nutr 2020;60(6):1048–61. https://doi.org/10.1080/10408398.2018.1556580.
[7] Yan B, Chen X, Yuan Q, Zhou X. Sustainability in fresh agricultural product supply chain based on radio frequency identification under an emergency. Cent Eur J Oper Res 2020;28:1343–61. https://doi.org/10.1007/s10100-019-00657-6.
[8] Mok WK, Tan YX, Chen WN. Technology innovations for food security in Singapore: a case study of future food systems for an increasingly natural resource-scarce world. Trends Food Sci Technol 2020;102:155–68. https://doi.org/10.1016/j.tifs.2020.06.013.
[9] Kayikci Y, Demir S, Mangla SK, Subramanian N, Koc B. Data-driven optimal dynamic pricing strategy for reducing perishable food waste at retailers. J Clean Prod 2022;344:131068. https://doi.org/10.1016/j.jclepro.2022.131068.
[10] Kayikci Y, Gozacan N, Lafci C, Kazancoglu Y. A conceptual framework for food loss and waste in agri-food supply chains: circular economy perspective. In: Challenges and opportunities of circular economy in Agri-food sector. Springer; 2021. p. 41–53. https://doi.org/10.1007/978-981-16-3791-9_3.
[11] Cicatiello C, Franco S, Pancino B, Blasi E, Falasconi L. The dark side of retail food waste: evidences from in-store data. Resour Conserv Recycl 2017;125:273–81. https://doi.org/10.1016/j.resconrec.2017.06.010.
[12] Lee D, Tongarlak MH. Converting retail food waste into by-product. Eur J Oper Res 2017;257(3):944–56. https://doi.org/10.1016/j.ejor.2016.08.022.
[13] Moraes CC, de Oliveira Costa FH, Pereira CR, da Silva AL, Delai I. Retail food waste: mapping causes and reduction practices. J Clean Prod 2020;256:120124. https://doi.org/10.1016/j.jclepro.2020.120124.
[14] Kazancoglu I, Ozbiltekin-Pala M, Kazancoglu Y, Kumar P. Food waste management in the retail sector: challenges that hinder transition to circular economy. J Mater Cycles Waste Manag 2022;24(2):655–66. https://doi.org/10.1007/s10163-022-01350-8.
[15] Schanes K, Dobernig K, Gözet B. Food waste matters-A systematic review of household food waste practices and their policy implications. J Clean Prod 2018;182:978–91. https://doi.org/10.1016/j.jclepro.2018.02.030.
[16] Ekren BY, Mangla SK, Turhanlar EE, Kazancoglu Y, Li G. Lateral inventory share-based models for IoT-enabled E-commerce sustainable food supply networks. Comput Oper Res 2021;130:105237. https://doi.org/10.1016/j.cor.2021.105237.
[17] Skaf L, Franzese PP, Capone R, Buonocore E. Unfolding hidden environmental impacts of food waste: an assessment for fifteen countries of the world. J Clean Prod 2021;310:127523. https://doi.org/10.1016/j.jclepro.2021.127523.
[18] Everitt H, van der Werf P, Seabrook JA, Wray A, Gilliland JA. The quantity and composition of household food waste during the COVID-19 pandemic: a direct measurement study in Canada. Soc Econ Plann Sci 2021:101110. https://doi.org/10.1016/j.seps.2021.101110.
[19] Deloitte. Capturing value from the smart packaging revolution. White Paper, Deloitte insight. Available at: https://www2.deloitte.com/us/en/insights/industry/retail-distribution/smart-packaging-how-to-create-and-capture-value.html; 2018.
[20] Rizou M, Galanakis IM, Aldawoud TMS, Galanakis CM. Safety of foods, food supply chain and environment within the COVID-19 pandemic. Trends Food Sci Technol 2020;102:293–9. https://doi.org/10.1016/j.tifs.2020.06.008.
[21] O'Callaghan KAM, Kerry JP. Consumer attitudes towards the application of smart packaging technologies to cheese products. Food Packag Shelf Life 2016;9:1–9. https://doi.org/10.1016/j.fpsl.2016.05.001.
[22] Meherishi L, Narayana SA, Ranjani KS. Integrated product and packaging decisions with secondary packaging returns and protective packaging management. Eur J Oper Res 2021;292(3):930–52. https://doi.org/10.1016/j.ejor.2020.11.022.

[23] Bender KE, Badiger A, Roe BE, Shu Y, Qi D. Consumer behavior during the COVID-19 pandemic: an analysis of food purchasing and management behaviors in U.S. households through the lens of food system resilience. Soc Econ Plann Sci 2021: 101107. https://doi.org/10.1016/j.seps.2021.101107.
[24] Wohner B, Pauer E, Heinrich V, Tacker M. Packaging-related food losses and waste: an overview of drivers and issues. Sustainability 2019;11(1):264. https://doi.org/10.3390/su11010264.
[25] Chen S, Brahma S, Mackay J, Cao C, Aliakbarian B. The role of smart packaging system in food supply chain. J Food Sci 2020;85(3):517–25. https://doi.org/10.1111/1750-3841.15046.
[26] Damiani M, Pastorello T, Carlesso A, Tesser S, Semenzin E. Quantifying environmental implications of surplus food redistribution to reduce food waste. J Clean Prod 2021;289:125813. https://doi.org/10.1016/j.jclepro.2021.125813.
[27] Tonini D, Albizzati PF, Astrup TF. Environmental impacts of food waste: learnings and challenges from a case study on UK. Waste Manag 2018;76:744–66. https://doi.org/10.1016/j.wasman.2018.03.032.
[28] Biji KB, Ravishankar CN, Mohan CO, Srinivasa Gopal TK. Smart packaging systems for food applications: a review. J Food Sci Technol 2015;52:6125–35. https://doi.org/10.1007/s13197-015-1766-7.
[29] Adeyeye SAO. Food packaging and nanotechnology: safeguarding consumer health and safety. Nutr Food Sci 2019;49(6):1164–79. https://doi.org/10.1108/NFS-01-2019-0020.
[30] Lerch C, Gotsch M. Digitalised product-service systems in manufacturing firms: a case study analysis. Res Technol Manag 2015;58(5):45–52. https://doi.org/10.5437/08956308X5805357.
[31] Cenamor J, Sjödin DR, Parida V. Adopting a platform approach in servitisation: leveraging the value of digitalisation. Int J Prod Econ 2017;192:54–65. https://doi.org/10.1016/j.ijpe.2016.12.033.
[32] Lenka S, Parida V, Wincent J. Digitalisation capabilities as enablers of value co-creation in servitizing firms. Psychol Market 2017;34(1):92–100. https://doi.org/10.1002/mar.20975.
[33] Li X, Wang Z, Chen C-H, Zheng P. A data-driven reversible framework for achieving Sustainable Smart product-service systems. J Clean Prod 2021;279:123618. https://doi.org/10.1016/j.jclepro.2020.123618.
[34] Kayikci Y, Demir S, Koc B. IoT-freshness sensor data-driven price information system for food waste reduction in grocery retail stores. 12th and 13th July 2021, ISBN 978-0-85358-343-1. In: Proceedings of the 25th International Symposium on Logistics; 2021. p. 171–9 [Online Conference)].
[35] Vazquez-Martinez GA, Gonzalez-Compean JL, Sosa-Sosa VJ, Morales-Sandoval M, Perez JC. CloudChain: a novel distribution model for digital products based on supply chain principles. Int J Inf Manag 2018;39:90–103. https://doi.org/10.1016/j.ijinfomgt.2017.12.006.
[36] Mohebi E, Marquez L. Intelligent packaging in meat industry: an overview of existing solutions. J Food Sci Technol 2015;52:3947–64. https://doi.org/10.1007/s13197-014-1588-z.
[37] Alizadeh AM, Masoomian M, Shakooie M, Khajavi MZ, Farhoodi M. Trends and applications of intelligent packaging in dairy products: a review. Crit Rev Food Sci Nutr 2022;62(2):383–97. https://doi.org/10.1080/10408398.2020.1817847.
[38] Calegari LP, Avalone MC, Fettermann DC. Barriers and enablers to food mass customisation. J Agribus Dev Emerg Econ 2020;10(4):403–28. https://doi.org/10.1108/JADEE-08-2019-0116.
[39] Vallandingham LR, Yu Q, Sharma N, Strandhagen JW, Strandhagen JO. Grocery retail supply chain planning and control impact of consumer trends and enabling technologies. IFAC-PapersOnLine 2018;51(11):612–7. https://doi.org/10.1016/j.ifacol.2018.08.386.
[40] Yu Z, Jung D, Park S, Hu Y, Huang K, Rasco BA, Wang S, Ronholm J, Lu X, Chen J. Smart traceability for food safety. Crit Rev Food Sci Nutr 2022;62(4):905–16. https://doi.org/10.1080/10408398.2020.1830262.
[41] Belaud J-P, Prioux N, Vialle C, Sablayrolles C. Big data for agri-food 4.0: application to sustainability management for by-products supply chain. Comput Ind 2019;111:41–50. https://doi.org/10.1016/j.compind.2019.06.006.
[42] Kodan R, Parmar P, Pathania S. Internet of things for food sector: status quo and projected potential. Food Rev Int 2020;36(6):584–600. https://doi.org/10.1080/87559129.2019.1657442.
[43] Heising JK, Dekker M, Bartels PV, Tiny) Van Boekel MAJS. Monitoring the quality of perishable foods: opportunities for intelligent packaging. Crit Rev Food Sci Nutr 2013;54(5):645–54. https://doi.org/10.1080/10408398.2011.600477.
[44] Huang IY, Manning L, James KL, Grigoriadis V, Millington A, Wood V, Ward S. Food waste management: a review of retailers' business practices and their implications for sustainable value. J Clean Prod 2021;285:1–15. https://doi.org/10.1016/j.jclepro.2020.125484.
[45] Provost F, Fawcett T. Data science and its relationship to big data and data-driven decision making. Big Data 2013;1(1):51–9. https://doi.org/10.1089/big.2013.1508.
[46] Frishammar J, Richtnér A, Brattström A, Magnusson & M, Björk J. Opportunities and challenges in the new innovation landscape: implications for innovation auditing and innovation management. Eur Manag J 2019;37:151–64. https://doi.org/10.1016/j.emj.2018.05.002.
[47] Pirola F, Boucher X, Wiesner S, Pezzotta G. Digital technologies in product-service systems: a literature review and a research agenda. Comput Ind 2020;123:103301. https://doi.org/10.1016/j.compind.2020.103301.
[48] Maleki E, Belkadi F, Bernard A. Industrial Product-Service System modelling base on Systems Engineering: application of sensor integration to support smart services. IFAC-PapersOnLine 2018;51:1586–91. https://doi.org/10.1016/j.ifacol.2018.08.270.
[49] Huang J, Li S, Thürer M. On the use of blockchain in industrial product service systems: a critical review and analysis. Procedia CIRP 2019:552–6. https://doi.org/10.1016/j.procir.2019.03.117.
[50] Kayikci Y, Usar DD, Aylak BL. Using Blockchain technology to drive operational excellence in perishable food supply chains during outbreaks. Int J Logist Manag 2021. https://doi.org/10.1108/IJLM-01-2021-0027.
[51] Esheiba L, Elgammal A, El-Sharkawi ME. Recommendation framework for on-demand smart product customisation. In: ICEIS 2019 - Proceedings of the 21st International Conference on Enterprise Information Systems; 2019. p. 177–87. https://doi.org/10.5220/0007684401770187.
[52] Rymaszewska A, Helo P, Gunasekaran A. IoT powered servitisation of manufacturing – an exploratory case study. Int J Prod Econ 2017;192:92–105. https://doi.org/10.1016/j.ijpe.2017.02.016.
[53] Schroeder GN, Steinmetz C, Pereira CE, Espindola DB. Digital twin data modeling with automationML and a communication methodology for data exchange. IFAC-PapersOnLine 2016;49:12–7. https://doi.org/10.1016/j.ifacol.2016.11.115.
[54] Sohail M, Sun DW, Zhu Z. Recent developments in intelligent packaging for enhancing food quality and safety. Crit Rev Food Sci Nutr 2018;58(15):2650–62. https://doi.org/10.1080/10408398.2018.1449731.
[55] Yam KL, Takhistov PT, Miltz J. Intelligent packaging: concepts and applications. J Food Sci 2005;70(1). https://doi.org/10.1111/j.1365-2621.2005.tb09052.x.
[56] Wang J, Zhang M, Gao Z, Adhikari B. Smart storage technologies applied to fresh foods: a review. Crit Rev Food Sci Nutr 2018;58(16):2689–99. https://doi.org/10.1080/10408398.2017.1323722.
[57] Winkelhaus S, Grosse EH. Logistics 4.0: a systematic review towards a new logistics system. Int J Prod Res 2020;58(1):18–43. https://doi.org/10.1080/00207543.2019.1612964.
[58] Ghoshal G. Recent trends in active, smart, and intelligent packaging for food products. In: Grumezescu AM, Holban SM, editors. Food packaging and preservation. Academic Press; 2018. p. 343–74. https://doi.org/10.1016/b978-0-12-811516-9.00010-5.
[59] Wang S, Liu X, Yang M, Zhang Y, Xiang K, Tang R. Review of time temperature indicators as quality monitors in food packaging. Packag Technol Sci 2015;28(10):839–67. https://doi.org/10.1002/pts.2148.
[60] Ben-Daya M, Hassini E, Bahroun Z. Internet of things and supply chain management: a literature review. Int J Prod Res 2019;57(15–16):4719–42. https://doi.org/10.1080/00207543.2017.1402140.
[61] Gallo A, Accorsi R, Goh A, Hsiao H, Manzini R. A traceability-support system to control safety and sustainability indicators in food distribution. Food Control 2021;124:107866. https://doi.org/10.1016/j.foodcont.2021.107866.
[62] Göransson M, Jevinger A, Nilsson J. Shelf-life variations in pallet unit loads during perishable food supply chain distribution. Food Control 2018;84:552–60. https://doi.org/10.1016/j.foodcont.2017.08.027.
[63] Göransson M, Nilsson F, Jevinger A. Temperature performance and food shelf-life accuracy in cold food supply chains–Insights from multiple field studies. Food Control 2018;86:332–41. https://doi.org/10.1016/j.foodcont.2017.10.029.
[64] Janjarasskul T, Suppakul P. Active and intelligent packaging: the indication of quality and safety. Crit Rev Food Sci Nutr 2018;58(5):808–31. https://doi.org/10.1080/10408398.2016.1225278.
[65] Mohammadian E, Alizadeh Sani M, Jafari SM. Smart monitoring of gas/temperature changes within food packaging based on natural colorants. Compr Rev Food Sci Food Saf 2020;19(6):2885–931. https://doi.org/10.1111/1541-4337.12635.
[66] Ben-Daya M, Hassini E, Bahroun Z, Banimfreg BH. The role of internet of things in food supply chain quality management: a review. Qual Manag J 2021;28(1):17–40. https://doi.org/10.1080/10686967.2020.1838978.
[67] Burlea-Schiopoiu A, Ogarca RF, Barbu CM, Craciun L, Baloi IC, Mihai LS. The impact of COVID-19 pandemic on food waste behaviour of young people. J Clean Prod 2021;294:126333. https://doi.org/10.1016/j.jclepro.2021.126333.
[68] Amicarelli V, Lagioia G, Sampietro S, Bux C. Has the COVID-19 pandemic changed food waste perception and behavior? Evidence from Italian consumers. Socio-Economic Planning Sciences; 2021, 101095. https://doi.org/10.1016/j.seps.2021.101095.
[69] Principato L, Secondi L, Cicatiello C, Mattia G. Caring more about food: the unexpected positive effect of the Covid-19 lockdown on household food management and waste. Socio-Economic Planning Sciences; 2020, 100953. https://doi.org/10.1016/j.seps.2020.100953.
[70] Gholami-Zanjani SM, Jabalameli MS, Klibi W, Pishvaee MS. A robust location-inventory model for food supply chains operating under disruptions with ripple effects. Int J Prod Res 2021;59(1):301–24. https://doi.org/10.1080/00207543.2020.1834159.
[71] Brennan L, Langley S, Verghese K, Lockrey S, Ryder M, Francis C, Phan-Le NT, Hill A. The role of packaging in fighting food waste: a systematised review of consumer perceptions of packaging. J Clean Prod 2021;281:125276. https://doi.org/10.1016/j.jclepro.2020.125276.
[72] Sahin E, Zied Babai M, Dallery Y, Vaillant R. Ensuring supply chain safety through time temperature integrators. Int J Logist Manag 2007;18(1):102–24. https://doi.org/10.1108/09574090710748199.
[73] Heising JK, Claassen GDH, Dekker M. Options for reducing food waste by quality-controlled logistics using intelligent packaging along the supply chain. Food Addit Contam 2017;34(10):1672–80. https://doi.org/10.1080/19440049.2017.1315776.
[74] Nakhai I, Jafari S. Developing smart and active packaging of inventory model in drug supply chain for special diseases. Singapore: IEEE International Conference on Management of Innovation & Technology; 2010. p. 550–5. https://doi.org/10.1109/ICMIT.2010.5492762. 2010.

[75] Mou S, Robb DJ, DeHoratius N. Retail store operations: literature review and research directions. Eur J Oper Res 2018;265(2):399–422. https://doi.org/10.1016/j.ejor.2017.07.003.

[76] Kulikovskaja V, Aschemann-Witzel J. Food waste avoidance actions in food retailing: the case of Denmark. J Int Food & Agribus Mark 2017;29(4):328–45. https://doi.org/10.1080/08974438.2017.1350244.

[77] Teller C, Holweg C, Reiner G, Kotzab H. Retail store operations and food waste. J Clean Prod 2018;185:981–97. https://doi.org/10.1016/j.jclepro.2018.02.280.

[78] Fan T, Xu C, Tao F. Dynamic pricing and replenishment policy for fresh produce. Comput Ind Eng 2020;139:106127. https://doi.org/10.1016/j.cie.2019.106127.

[79] Liu X, Tang O, Huang P. Dynamics pricing and ordering decision for the perishable food of the supermarket using RFID technology. Asia Pac J Market Logist 2008;20(1):7–22. https://doi.org/10.1108/13555850810844841.

[80] Wang X, Li D. A dynamic product quality evaluation-based pricing model for perishable food supply chains. Omega 2012;40:906–17. https://doi.org/10.1016/j.omega.2012.02.001.

[81] Herbon A, Levner E, Cheng TCE. Perishable inventory management with dynamic pricing using time–temperature indicators linked to automatic detecting devices. Int J Prod Econ 2014;147:605–13. https://doi.org/10.1016/j.ijpe.2013.07.021.

[82] Li D, Wang X. Dynamic supply chain decisions based on networked sensor data: an application in the chilled food retail chain. Int J Prod Res 2017;55(17):5127–41. https://doi.org/10.1080/00207543.2015.1047976.

[83] Aytac K, Korçak O. IoT based intelligence for proactive waste management in Quick Service Restaurants. J Clean Prod 2021;284:125401. https://doi.org/10.1016/j.jclepro.2020.125401.

[84] Power DJ. Understanding data-driven decision support systems. Inf Syst Manag 2008;25(2):149–54. https://doi.org/10.1080/10580530801941124.

[85] Awan U, Shamim S, Khan Z, Zia NU, Shariq SM, Khan MN. Big data analytics capability and decision-making: the role of data-driven insight on circular economy performance. Technol Forecast Soc Change 2021;168:120766. https://doi.org/10.1016/j.techfore.2021.120766.

[86] Huber J, Gossmann A, Stuckenschmidt H. Cluster-based hierarchical demand forecasting for perishable goods. Expert Syst Appl 2017;76:140–51. https://doi.org/10.1016/j.eswa.2017.01.022.

[87] Abideen AZ, Sundram VPK, Pyeman J, Othman AK, Sorooshian S. Digital twin integrated reinforced learning in supply chain and logistics. Logistics 2021;5(4):84. https://doi.org/10.3390/logistics5040084.

[88] Dye CY. Optimal joint dynamic pricing, advertising and inventory control model for perishable items with psychic stock effect. Eur J Oper Res 2020;283(2):576–87. https://doi.org/10.1016/j.ejor.2019.11.008.

[89] Feng L. Dynamic pricing, quality investment, and replenishment model for perishable items. Int Trans Oper Res 2019;26(4):1558–75. https://doi.org/10.1111/itor.12505.

[90] Buisman ME, Haijema R, Bloemhof-Ruwaard JM. Discounting and dynamic shelf life to reduce fresh food waste at retailers. Int J Prod Econ 2019;209:274–84. https://doi.org/10.1016/j.ijpe.2017.07.016.

[91] Chen J, Dong M, Rong Y, Yang L. Dynamic pricing for deteriorating products with menu cost. Omega 2018;75:13–26. https://doi.org/10.1016/j.omega.2017.02.001.

[92] Das R, Barman A, De PK. Integration of pricing and inventory decisions of deteriorating item in a decentralised supply chain: a Stackelberg-game approach. Int J Syst Assurance Eng Manag 2022;13(1):479–93. https://doi.org/10.1007/s13198-021-01299-1.

[93] Huang H, He Y, Li D. Pricing and inventory decisions in the food supply chain with production disruption and controllable deterioration. J Clean Prod 2018;180:280–96. https://doi.org/10.1016/j.jclepro.2018.01.152.

[94] Tiwari S, Jaggi CK, Gupta M, Cárdenas-Barrón LE. Optimal pricing and lot-sizing policy for supply chain system with deteriorating items under limited storage capacity. Int J Prod Econ 2018;200:278–90. https://doi.org/10.1016/j.ijpe.2018.03.019.

[95] Keskin NB, Li Y, Song JS. Data-driven dynamic pricing and ordering with perishable inventory in a changing environment. Manag Sci 2022;68(3):1938–58.

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