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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 & Tongarlik [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 waste in Japan and...
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 [6]. 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 servitization [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 [35,35]. 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 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 perishable supplies. The results showed that smart 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 are being transformed 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 [3]; (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, antithief, 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 decide 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 complicate 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 loses 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.
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. 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. 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.

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 34 (four factors with three levels) x 10 (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 demonstrative.
Fig. 3. The flow chart of the proposed model.
Considering the average daily profit performance metric, the significant
of Variance (ANOVA), where the level of significance is selected as 0.05.
food waste.
this experiment. According to the ANOVA analysis, none of the in
randomly assigned if the customer
freshness, the customer
priority attribute is determined as
its priority attribute is randomly
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 de-
viation 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 dis-
counts. Table 2 presents the p-values of the factorial fit ANOVA table for
this experiment. According to the ANOVA analysis, none of the in-
teractions is significant.

| Table 2 |
|-------------------------|
| 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%) |

The simulation study revealed that the average daily profit is maxi-
mised, 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
capacity 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 cus-
tomers. 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%)
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.

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 condi-
tions 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 main factors are 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 quan-
tity discounts also has a large effect on the model. Fig. 6 shows the ef-
fects of these interactions on the average daily rejected customers. Stock
capacities of 125 for all pack sizes minimise the daily rejected cus-
tomers. 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.
Smart packaging systems have 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 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.

### Table 3

| 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 | 0.369 |
| Stock Capacities*Freshness Periods*Quantity Discounts | 0.612 |
| 4-Way Interactions | 0.126 |
| Stock Capacities*Freshness Discount Rate*Freshness Periods*Quantity Discounts | 0.126 |

### Fig. 4.

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

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...
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

![Fig. 5. Significant main effects for average daily total waste response.](image1)

![Table 4](image2)

| 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   |

![Fig. 6. Significant interaction effects for avg. percentage of daily rejected customers response.](image3)

![a) Stock Capacities*Quantity Discounts](image4)

![b) Freshness Discounts*Quantity Discounts](image5)

![Table 5](image6)

| 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%) |
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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