Smart Retailing: a model to assess the economic sustainability of smart shelf-enabled dynamic pricing

Vadruccio R.*, Siragusa C.*, Guglielmetti C.* and Tumino A.*

* *Dipartimento di Ingegneria Gestionale (DIG), Politecnico di Milano, Via Lambruschini, 4B 20156 – Milano – Italy (roberta.vadruccio@polimi.it, chiara.siragusa@polimi.it, cecilia.guglielmetti@polimi.it, angela.tumino@polimi.it)*

Abstract: Smart Retailing, a new approach to retail management that leverages digital technologies, is gaining much attention, as it enables innovation and improvements in consumers' quality of life. However, the potentialities stemming from the application of such technologies are still not fully explored. Investment analyses addressing specific technologies could be useful to fill the academic gaps and guide retailers in their digital transition. This paper aims thus at evaluating the economic sustainability of investment in smart shelves, which are employed to perform dynamic pricing in presence of perishable goods. A model simulating the pricing variation in different scenarios was built and economic and financial analyses were performed to evaluate the sustainability of the investment. Data to feed the model were collected through semi-structured interviews with a smart shelf technology provider and three grocery retailers. The results show that the employment of smart shelves allows retailers to increase their profits. First, they are always able to assign to the product the price which most accurately reflects the customers' willingness to pay. Second, the costs related to misplacement issues are reduced. This study contributes to the knowledge in this unexplored field by providing a model that simulates the dynamic pricing policy after the introduction of smart shelf technology and evaluates its economical sustainability. It also provides retailers who want to join the digital transformation of the stores with a useful tool to guide their investments.

Keywords: Smart Retailing, smart shelf, dynamic pricing

I. Introduction

The Smart Retailing phenomenon, a new approach to retail management that leverages digital technologies, is gaining much attention, as it enables innovation and improvements in consumers' quality of life [1]. Indeed, it represents an effective way to answer the socio-economic changes that are affecting the retail sector. They can be summarised in the ever-changing customers' preferences [2], the intense technological evolution [3], the strong omnichannel integration [4].

Therefore, Smart Retailing emerges as a fruitful way to meet these challenges. This is also highlighted by the extensive literature present in the field. Nevertheless, there is still room for research, especially considering the most innovative technologies (e.g., smart mirrors, smart shelves, smart carts, …) and related economic benefits for retailers. Among them, smart shelves deserve high attention, given the potential stemming from their in-store application.

Smart shelves are electronically connected shelves that can be used for four main purposes. First, they allow retailers to enhance inventory management, by keeping track of the items exhibited on them and automatically sending a notification to store personnel when the last item is removed [5], [6]. Second, smart shelf enables personalised proximity-marketing activities directed to the customers, exploiting Bluetooth technology. Indeed, it can send messages when shoppers are in its proximity, triggering advertising notifications or app actions on shoppers' smartphones [5]. Third, this technology can bridge the online and the offline channels, allowing shoppers to browse the shelves the same as online browsing getting the same comprehensive or comparative information about products [7]. Fourth, thanks to the digital label present on the shelf, this technology allows real-time price management, enabling dynamic pricing activities. This task could follow different logic. Price could vary according to the expiration date of the article, the quantity present in the store's warehouse or the customers' willingness to pay [5].

This work concentrates then on this last kind of usage. In particular, the application of this pricing policy is simulated in a grocery retailer, in presence of perishable goods, whose quality deteriorates within a short time, such as fresh agricultural products. They are also high-frequency rigid demand products in daily life and occupy an important position in the retail consumer market [8]. Therefore, dynamic pricing policies can be remarkably effective on this kind of goods, as when they approach their expiry date, consumer willingness to pay for them diminishes because of the perceived augmented risk to freshness [9]. In addition, this pricing policy could produce benefits related to food sustainability, by reducing the food waste. Goods could be sold to consumers at a lower price instead of remaining unsold and therefore going wasted [10].

This work aims thus at evaluating the sustainability of investment in smart shelves employed to perform dynamic pricing, by leveraging on a model simulating the pricing variation in different scenarios.

The paper is organized as follows. Section 2 displays the outcomes of the literature review, conducted in the field of smart shelves and dynamic pricing, respectively, section 3 identifies the objectives and the methodology adopted, section 4 describes the model development, section 5 provides the model application and the sensitivity analysis, and section 6 summarizes the evidence found and conclusions of the work.

II. LITERATURE REVIEW

Smart shelf is a versatile technology, suitable for very different activities, as explained above. For this reason, several scholars have studied the phenomenon from different perspectives. Some of them tried to summarise the characteristics and the benefits stemming from the application of this technology, as in the work of Inman & Nikolova (2017). They initially introduced, among the others, the smart shelf technology, and then investigate customers’ attitudes towards it, in order to provide retailers with insights on its adoption. With the same objective, Kellermayr-Scheucher et al. (2021) provided an overview of the various intelligent shelf technologies available and the related technological functionalities. In particular, the main purpose was to provide grocery retailers with information on which articles and assortments smart shelves are suitable for and which further developments are planned from technology providers.

On the other side, many authors carried out some experiments aiming at evaluating certain characteristics of smart shelves in different contexts and for different purposes. For example, Rashid et al. (2015) presented an experiment aimed at understanding the dynamics of online-offline interaction in presence of smart shelves, by allowing customers to browse objects placed on a shelf in a retail store, obtaining the same comprehensive and thorough information about them one would expect from browsing about the same products in an online store, but with actually touching them or otherwise physically interacting with them. In the work of Low & Clifford Lee (2021) a smart shop was designed with the purpose of being without staff and convenient, using smart shelves technology to detect items picked by customers and charge them accordingly. The goal of the experiment of Melià-Seguí & Pous (2014) was, instead, to detect human-object interaction in presence of smart shelves and items tagged with RFID (Radio Frequency Identification), in order to extract meaning and value from it that could be used for retail intelligence. Or Zhu et al. (2018) proposed an RFID-enabled smart shelf inventory control system and conducted a cost-benefit analysis of this system. In particular, the study analysed the optimal policy of retailers that are subject to inventory inaccuracy, by comparing the cycle counting with the RFID-enabled smart shelf inventory control system.

Anyway, few authors investigated the effects of adopting the smart shelf technology to allow dynamic pricing policies. Among them, Stamatopoulos et al. (2021) focused on price adjustment costs (i.e., menu costs), which are considered by experts to be one of the primary reasons why dynamic pricing has not yet been extensively used by brick-and-mortar retailers, proving that they could be significantly reduced with the adoption of electronic shelf label. However, none of them made investment analyses on smart shelf technology in presence of dynamic pricing.

Focusing on the research on dynamic pricing, there is an extensive literature in this field. Many authors attempted to study this policy considering different logic. For example, considering the case of perishable food, Chen et al. (2018) explored the optimal price structure when menu costs are considered. Wang et al. (2015) considered the case of a multiperiod perishable pricing strategy considering consumers’ price fairness perception. While Chung & Li (2014) identified the economic benefits of employing a pricing policy that more dynamically matches food shelf-life change and encourages consumers’ consumption-need driven purchases. In the work of Zhou et al. (2009) an item-level dynamic pricing scheme was developed, focusing on the current set of consumers on the shop floor and their characteristics, preferences, etc. Golrezaei et al. (2020) characterised a profit-optimal selling mechanism for a firm with customers who have heterogeneous valuations of items that decrease in a heterogeneous fashion. Lastly, Xiao et al. (2019), considered a dynamic pricing scheme in which the retailer offers two prices, at the beginning of the advance period and the spot period, respectively.

Based on the above, it is possible to highlight that the literature provides no evidence on financial and economic analysis aimed at understanding the return on the investment on smart shelf technology where dynamic pricing policies are applied. Nevertheless, this kind of study could significantly help retailers evaluate the investments necessary for the digital transformation of the store.

III. OBJECTIVES AND METHODOLOGY

Given the gap present in the existing body of knowledge, this paper aims at evaluating the economic sustainability of investments in smart shelf technology, used for dynamic pricing activities in presence of perishable goods.

Specifically, the objective is to simulate the price variation over time in relation to the expiring date, which is automatically performed by the smart shelves thanks to the in-built technology. On top of the simulation, a financial analysis is carried out to evaluate the sustainability of the investment.

The work was organised as follows. (i) The main variables to be considered when applying this pricing policy were identified. (ii) A model replicating the price variation according to the expiring date was developed. (iii) The analytical model for the estimation of the policy profitability was built. (iv) The model was applied to a real case scenario of a grocery retailer. (v) A sensitivity analysis on relevant parameters was run, in order to test the reliability of the outcomes of the model application, and the robustness of the model itself.

The main methods adopted in the research to support the model development and application are the following. (1) Literature review, in order to investigate smart shelves characteristics and usage, and dynamic pricing models. (2) Semi-structured interviews with three Italian retailers operating in the grocery sector, to gather data for the model application and the validation of the results obtained. In particular, the main information collected relates to the product price, the purchasing and ordering costs, the number of units sold and product misplacement rates. An interview was conducted also with a smart shelf technology provider to collect information on the installation and operating cost and the characteristics of the solution.

IV. Model development

The model consists of a simulation of the price evolution over time, in the presence or not of a smart shelf, and provides for an economical evaluation of the pricing policy, by comparing the profits gained through the solution with the cost of the investment. In this work, the technological infrastructure taken into consideration consists of smart shelves enabled by cameras, computer vision and Artificial Intelligence (AI), and equipped with LED displays. This kind of solution was preferred instead of an RFID system mainly for a financial reason. The cost of a single RFID tag, which generally is around 15 cents, cannot be justified by a perishable product that is typically sold at a low price and has a very short lifetime. On the other hand, the employment of AI-powered cameras above shelves allows to easily train algorithms able to recognise any kind of product and does not require any sensor applied on single products.

The elements involved in the model building can be summarised according to the scheme displayed in Figure 1.

Input data refer to variables that can be set by the retailer, while context data report market characteristics. The algorithm calculates the demand function according to the pricing policy, giving as output the profitability and investment analysis.

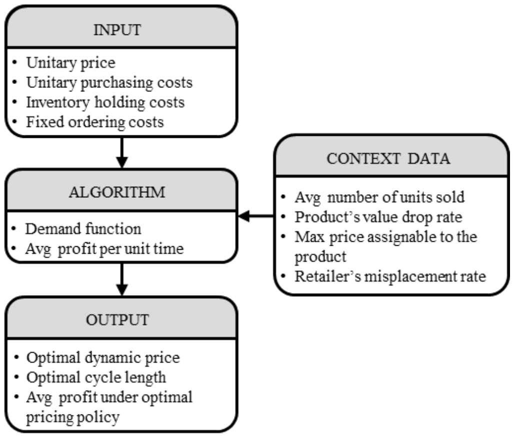

Fig. 1.Model building blocks

The dynamic pricing activity is performed according to the expiration date of the product present on the shelves. The model is developed by comparing two alternative situations for the same retailer, who faces a known demand function. In one case, the retailer is endowed with smart shelves and, thus, it is able to implement the dynamic pricing strategy. In the other, no smart shelves are employed, constituting the current situation of retailers in which prices are fixed over longer time intervals. Additionally, when smart shelves are not in place, the retailer is assumed to face misplacement issues which result in lower on-shelf availability and lost sales. These issues are solved almost in real-time and become negligible when smart shelves are employed.

Below are reported the main assumptions made for the model development.

- The retailer sells a single product. In fact, even if considering multiple products that do not share resources the problem can be separable into a single product case [21].
- The retailer faces no competition.
- The product is perishable and, thus, its value decreases over time. The demand takes into account this circumstance by including a function representing the value drop.
- The retailer, when smart shelves are not employed, experiences issues from product misplacement and out-of-shelves situations, which are modelled as an extra cost [13].
- The model is developed for a time horizon corresponding to a single inventory cycle.
- The replenishment lead time is considered negligible without loss of generality [22].
- The demand faced by the retailer is deterministic and it depends on price and time.

In the presence or not of smart shelves, an optimization problem is solved, in which the objective function is the average profit per unit time. The expression is maximized with respect to the price and to the cycle length, thus, the outputs of the model are both the optimal price, expressed as a function of time, and the optimal cycle length. Therefore, the following expression is maximized in presence of smart shelf.

$$\Pi(\theta, p(\cdot)) = \frac{1}{\theta}\left[\int_0^{\theta}\{(p(t) - c - ht)\cdot D(p(t),t)\}\,dt - K\right] \quad (1)$$

In this formula, θ is the cycle length, *p(t)* is the selling price per unit at time t, *c* is the variable cost for each unit ordered, *h* is the inventory holding cost per unit per time unit and *K* is the fixed ordering cost. The expression *p(t)-c-ht* is the retailer's per unit contribution margin at time *t*, computed as the selling price per unit minus the total unit cost. Here, *c+ht* is the total unit cost. Considering the case in which smart shelves are not in place, the product loss rate cost is introduced in the average profit formula, representing an extra cost for the retailer.

In further detail, the solved optimization problem is based on the guidelines provided by Rajan et al. (1992) in their dynamic pricing model for a perishable item. The demand function is then represented as follows.

$$D(p,t) = \begin{cases} \dfrac{a - p\cdot\lambda(t)}{b} & for \quad 0 \le p \le \dfrac{a}{\lambda(t)} \\ 0 & for \quad p > \dfrac{a}{\lambda(t)} \end{cases} \quad (2)$$

Where *a* is the minimum price over which demand would be zero at time zero, *a/b* is the total market potential, i.e. the demand that would be captured with zero price, and *λ(t)* is the value drop rate, modelled as a discount on the maximum price the customers are willing to pay. Thus, *1/λ(t)* is the percentage of the remaining value of the product over time. *λ(t)* can assume different functional forms. The authors provided the calculations in the case of exponential value drop, where the function assumes the following form.

$\lambda(t) = e^{\mu t}$ where $\mu \geq 0$ (3)

The economic evaluation of the investment was performed by considering the following indicators.

1. *Payback time*, which refers to the amount of time it takes to recover the cost of an investment.

Payback time=Investment/Δprofits (4)

where Δprofits=avg daily profits with smart shelves-avg daily profits with no smart shelves (5)

2. *ROI.* Annual ROI was considered.

ROI=(Δprofits ·#days per year)/Investment (6)

V. Model Application and Results

A. Base case scenario

The model was applied to a base case scenario of a medium-sized supermarket, defined through interviews and market analysis. The product considered as a reference unit is a yogurt package including two pots of 125 grams. This kind of food was regarded as one of the most appropriate for the implementation of the model, since it lasts for about 6 weeks, and perfectly matches the purpose for which the smart shelf solution is adopted.

The main parameters used as input for the model are presented in Table 1.

TABLE I
Input Parameters of the Baseline Scenario

Parameter	Value	Definition
$\frac{a}{b}$	500	Average quantity sold per day (units)
a	3	Minimum price (€) over which demand would be driven to zero at any time
c	1.1	Unitary cost (€) of buying the product from supplier
K	10	Fixed ordering cost (€)
σ	0.05	Product loss rate due to misplacement
μ	0.035	Parameter of the value drop function

The cycle length for the reordering policy is assumed equal to 7 days. While for the smart shelf case the prices constantly decrease over time, for the traditional shelf scenario the discount is applied on day 5 of the cycle. It is important to underline that, in a real application, it would not be reasonable to apply a discount on yogurts when they are only 5 days old. However, in real situations, not all the yogurts from previous cycles are sold before beginning a new cycle. Typically, when retailers receive new units of yogurt, they place them in the back of the refrigerator, in order to make people buy the older units before. However, customers are aware of this, and they always grab the products with the longest expiry date. Thus, the retailer ends up with some units of product that are actually approaching expiration and must discount them. For this reason, it is reasonable to consider, also for short cycles, that there is a point in time in which the retailer does the discount.

Figure 2 shows the first outputs of the model, which are the optimal prices that the retailer would assign over the considered cycle, for smart shelves (black line) and traditional shelves (grey line), respectively.

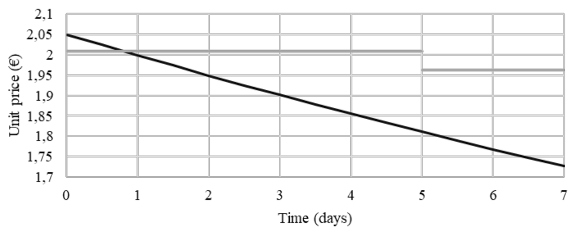

Fig. 2. Prices in the baseline scenario

The prices assigned by the retailer in the absence of smart shelves are higher in order to cope with the increased product loss rate. Additionally, the discount the retailer would make on day 5 is very small. In the first five days the price would be 2€ and, in the last two days, 1.96€.

Figure 3 shows the instantaneous margins in the two cases (smart shelves in black line and traditional shelves in grey line). Notably, the margins are always higher when smart shelves are employed.

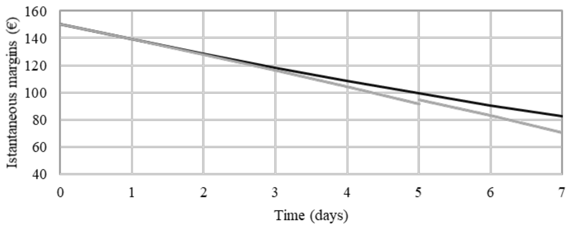

Fig. 3. Instantaneous margins in the baseline scenario

Table 2 shows the average profits per day and per unit in the two cases.

TABLE II
AVERAGE PROFITS IN THE BASELINE SCENARIO

	No smart shelves	Smart shelves	Extra profits
Average profits per day (€)	85.47	113	27.53
Average profits per unit (€)	0.17	0.23	0.06

When smart shelves are employed, the average daily profit is equal to 113 €. On the other hand, without smart shelves, the average profits decrease to 85.47€. Thus, smart shelves provide retailers with an extra profit equal to 27.53 € per day.

For the computation of the cost of the investment, the following assumptions were made, according to the retailers' interview. It is assumed that the retailer owns a big backroom space where to stock the items. Thus, the retailer does not need to apply the same proportion between the number of units sold and the length of smart shelves needed.

So, assuming that the retailer places in the store's refrigerator a number of yogurts that exceeds the average quantity sold by 50% of its value per day, to make sure that, with daily replenishment from the backroom, there is no risk of out-of-shelf. Thus, considering the 150% of the average units sold per day, the retailer will need a space in the store's refrigerator able to contain 750 yogurts. Each unit of yogurt is around 20 cm long, and it is possible to stock around 18/20 units in each column of yogurt exposed in the fridge. Hence, the retailer will need around 40 rows, which correspond to a length of 800 cm, or 8 meters.

Since the cost of the investment for each meter of smart shelf is estimated at around 700€, according to the smart shelf provider, the cost of the investment in 8 meters of smart shelves is the following.

Investment=700·8=5600€

For what concerns the computation of the financial indexes useful to evaluate the investment, it is important to underline that a medium-sized retailer is typically open 7 days a week and, during the year, it closes only during official holidays. Hence, we consider a number of opening days per year equal to 350 days. Therefore, in the baseline scenario, the financial indexes are worth as follows.

$$Payback\ time = \frac{Investment}{\Delta profits} = \frac{5600}{27.53} = 203\ days \cong 7\ months$$

$$ROI = \frac{\Delta profits\ \cdot 350}{Investment} = \frac{27.53 \cdot 350}{5600} = 1.72$$

The indexes prove the convenience of the solution in the case considered, as the investment could be recovered in just seven months. As another piece of evidence, the ROI index is largely higher than 1, meaning that the retailer is creating value.

B. Sensitivity analysis

Afterwards, a sensitivity analysis was performed by varying some input parameters. In particular, the main parameter changed refers to the size of the supermarket. Changing the size of the retailer means varying the average units sold per day, the cost of investment in the technology, the length of the cycle, the fixed ordering costs and product loss rate due to misplacement.

It is indeed possible to assume that retailers of different sizes have different product loss rates. In fact, in the case of a small retailer, it is simpler to keep track of all the movements of products from the backroom to the salesfloor and around the salesfloor. A bigger retailer, on the other hand, with no dedicated technology in place, will not be able to keep such an accurate track of the products and, additionally, it will have a higher influx of customers which might cause misplacement.

The objective of the sensitivity analysis is therefore to assess the profitability of the solution concerning different kinds of retailers. Firstly, a smaller supermarket was considered. The average quantity sold per day (a/b) is now equal to 20 units, and the product loss rate (σ) decreases to 0.01.

Also, in this case, a cycle length equal to 7 days is considered, and the discount in the traditional shelf scenario is applied on the fifth day as well. Table 3 reports the profitability in this scenario.

TABLE III
AVERAGE PROFITS IN THE SMALL RETAILER SCENARIO

	No smart shelves	Smart shelves	Extra profits
Average profits per day (€)	2.91	3.15	0.24
Average profits per unit (€)	0.15	0.16	0.01

In this case, it is sufficient to reserve approximately 60 cm of length in the fridge for the yogurts' storage. Thus, the investment the retailer should make in smart shelves for the yogurt would be around 420€. Notice that this would not be the real cost of implementing 60 cm of smart shelves, but it is estimated by considering the fact that, in a real application, a retailer would not invest in just 60 cm of shelves, but in a sufficient length, such that the investment for those 60 cms would be around 420€.

The payback time is then estimated as follows.

$$Payback\ time = \frac{Investment}{\Delta profits} = \frac{420}{0.24} = 1750\ days \cong 5\ years\ and\ 10\ months$$

For the computation of the ROI, a number of opening days per year equal to 300 days was considered. Indeed, small retailers are usually closed on Sundays.

$$ROI = \frac{\Delta profits \cdot 300}{Investment} = \frac{0.24 \cdot 300}{420} = 0.17$$

Even if the ROI is positive, meaning that the investment is recovered, the payback time is quite long. Indeed, the extra profit gained from the implementation of smart shelves is not so significant, and it results in poor financial indicators.

Considering, instead, a bigger retailer, the average quantity sold per day (a/b) raises to 2000 units, and the product loss rate (σ) is equal to 0.10. It is worth highlighting that the fixed ordering cost (K) raises to 100€ in this case, differing from the other scenarios. Indeed, in light of the unit purchased in every order by the big retailer, this amount better reflects what happens in reality.

In this case, it is reasonable to assume that the retailer does replenishment more frequently because stocking such a high quantity of units in the backroom would not be feasible. Indeed, the optimal cycle length when smart shelves are employed is 2 days, as suggested by the model itself. In this situation, the price assigned to the item is kept fixed in absence of smart shelves, while when smart shelves are employed, it decreases by 5% during the cycle. It is interesting to underline that the price assigned in case of the absence of smart shelves is always higher than the optimal price when smart shelves are employed. The reason why is that the retailer is trying to recover the costs of product misplacement by increasing the prices.

Table 4 reports the average profit of the retailer in this scenario.

TABLE IV
AVERAGE PROFITS IN THE BIG RETAILER SCENARIO

	No smart shelves	**Smart shelves**	**Extra profits**
Average profits per day (€)	444.31	507.23	62.92
Average profits per unit (€)	0.22	0.25	0.03

For what concerns the cost of the investment in smart shelves, a calculation similar to the previous cases can be made. The hypothesized length of shelves needed will be around 30 meters and the opening days of the store are 350. Therefore, the financial indicators worth as follows.

$$Payback\ time = \frac{Investment}{\Delta profits} = \frac{21000}{62.92} = 334\ days \cong 11\ months$$

$$ROI = \frac{\Delta profits \cdot 350}{Investment} = \frac{62.92 \cdot 350}{21000} = 1.05$$

The situation is considerably improved compared with the case of the small retailer, as proven by the financial indicators, which are similar to those of the medium-sized retailer. The investment is, therefore, economically convenient.

VI. Conclusions

The analysis developed in this study aimed at evaluating the economic sustainability of smart shelf applications employed to perform dynamic pricing in different scenarios.

By looking at the results, it is possible to observe that the employment of smart shelves for dynamic pricing always results in higher profits. The reason is twofold. On one hand, with smart shelves in place, the retailer is always able to assign to the product the price which most accurately reflects the willingness to pay of the customers. On the other, the retailer with no smart shelves faces an additional cost related to misplacement, which results in a decrease in the average profits. In particular, the retailer of medium and big size are the ones that most benefit from the implementation of the solution, as observable from the financial indicators. This is mainly related to the optimization of inventory management given the lower misplacement occurrence in presence of smart shelf, rather than to the dynamic pricing policy. Indeed, this policy actually enables a slight price change during the cycle. This is also connected to the inventory replenishment occurrence, which is more frequent for big retailers compared to small retailers. Hence, a proper dynamic pricing strategy is difficult to model when cycles are short. Thus, big retailers facing considerable misplacement issues can benefit the most from the technology, even if a proper dynamic pricing policy is not performed.

Concerning the main contributions of the works, they can be summarised as follows. From the academic perspective, it provides a model that replicates the dynamic pricing policy in presence of perishable products, used to evaluate the economical sustainability of the investment in smart shelf technology. Its application considering different scenarios enabled an in-depth understanding of the initiative in relation to different kinds of retailers. This work represents an innovation with respect to the models already present in literature as it considers the technological infrastructure needed to implement such a strategy in a physical store, which is typically overlooked. The process represented is simplified compared to what happens in reality, but it allows the evaluation of the dynamics involved. Regarding the managerial contribution, the proposed model provides useful insights for retailers who want to implement smart shelf technology in-store, evaluating the convenience of the investment.

However, this work presents some limitations, mainly related to the necessary hypotheses considered to develop the model, which allowed to decrease the level of complexity but, in some cases, distanced the model from reality.

The investment estimation takes into account only those costs related to the purchase of the technology.

However, the investment typically involves collateral costs, such as administrative or maintenance costs, which should be evaluated for a comprehensive view of the cost structure.

The benefits stemming from the employment of smart shelves are limited to the execution of dynamic pricing and, secondarily, to the identification of misplaced products. However, such technology can be employed for a multitude of purposes, from demand forecasting improvement to cross and up-selling activities. Hence, the model is only partially assessing the profitability of employing such a solution and, as a consequence, the economical sustainability is underestimated.

The model does not contemplate the possibility to make the inventory replenishment before the product gets out of stock, which would mean modelling the demand for the same product at different levels of freshness and implementing dynamic pricing for that product. However, by contemplating this situation the model would better adhere to reality.

It is assumed that the demand function is perfectly elastic. Nevertheless, this could not be true as customers may perceive the continuous changes in the price negatively. Therefore, an in-depth understanding of customer behaviour could fix this issue.

In addition, smart shelf adoption could introduce benefits related to food sustainability. In fact, strategically pricing perishable products over their lifespan encourages customers to buy them before they spoil. Applied on a larger scale, this solution might be able to decrease the amount of food waste. Therefore, future development of this work could aim at evaluating the investment by adopting this complementary perspective.

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