ISSN 1611-1699 / eISSN 2029-4433

VILNIUS TECH
Vilnius Gediminas Technical University

JOURNAL of BUSINESS ECONOMICS & MANAGEMENT

2025
Volume 26
Issue 1
Pages 127–144
https://doi.org/10.3846/jbem.2025.22952

DECISION SUPPORT ALGORITHM DEVELOPMENT FOR ASSORTMENT OPTIMIZATION IN THE RETAIL CHAIN

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Article History:
- received 12 June 2024
- accepted 18 November 2024

Abstract. As the consumer market changes rapidly, retail networks require a system to optimize the quantity and assortment of goods. The authors develop and test theoretical and practical assortment optimization and distribution principles. The study aims to improve retail assortment management by creating a decision support system for optimizing commodity composition, quantity, and location. The system's primary objective is to enhance the trading margin obtained from the sale while considering constraints related to commodity resources and shelf space. This entails optimizing the procurement and inventory management processes to maximize the profit margin. By generating freight invoices, distributing, and redistributing commodities within the network under inbound logistics orders, the system optimizes the allocation of commodities using information from the company's existing software. The authors present an optimization method for commodities that relies on mathematical modeling and the calculation of the consolidated profitability ratio. It ensures the necessary accuracy and provides assortment management within time and cost limits, without substantial investments in equipment and updating qualifications of employees. The research outcomes are applicable to apparel retail. The practical outcome is maximizing the return on investment for goods sold per day. The algorithm's benefits and effectiveness were calculated based on real data after implementation.

Keywords: retail chain, assortment optimization, assortment management, commodity management, decision support system, apparel retail, sales analytics, business processing.

JEL Classification: M21, L14, L21.

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1. Introduction

The retail landscape has undergone significant transformations in recent years, driven by dynamic consumer preferences, technological advancements, and external shocks such as the COVID-19 pandemic (Basit et al., 2023). Retail chains must adapt swiftly to remain competitive and profitable. This prioritizes the need for assortment policy efficiency and highlights the gaps in existing literature. Retailers invest substantial resources in their product assortments, aiming to meet customer demands while optimizing profitability. However, the current global context, marked by supply chain disruptions, shifting consumer behavior, and economic uncertainties, necessitates a reevaluation of traditional approaches.

The pandemic has exacerbated these challenges, constraining physical store operations, altering demand patterns, and affecting supply availability. Retailers must navigate these complexities to thrive in the post-pandemic era (Jasińska-Biliczak, 2022; Kasprzak, 2020). The solution to this problem may be a more efficient use of existing resources based on their redistribution. However, effective assortment management requires the analytical processing of vast amounts of data. Retailers must identify high-performing products, allocate shelf space efficiently, and align pricing strategies with market dynamics. Retail networks must swiftly adapt assortments based on real-time insights, anticipating shifts in consumer preferences and external factors.

According to Kahn (1999), "configuring and pricing the product assortment offered" is a central issue in retail operations management. However, the literature analysis shows insufficient knowledge about the practical application of systems, that can help decision-making (Oh et al., 2023). Despite the theoretical groundwork, practical implementation remains a challenge. Existing literature lacks comprehensive insights into decision support systems that aid assortment management. Retailers need actionable guidance on deploying systems that enhance decision-making (Hübner, 2017; Çömez-Dolgan et al., 2022).

Retailers seek the optimal mix of products to maximize revenue and profitability. The assortment optimization problem involves selecting products that resonate with consumers while minimizing costs. The Retail Commodity Management Shelf Space and Profit Planning (RCM SPP) framework, proposed by Iurasov (1998), addresses this challenge. However, its practical application remains underexplored (Bani Hani, 2022; Arsawan et al., 2023).

Our research aims to bridge the gap between theory and practice by designing a decision support system for assortment optimization using available resources. The creation of such an algorithm became possible due to the development of inexpensive and efficient mechanisms for processing big data. The goal of the article is to improve retail assortment management by developing a prototype algorithm for the Decision Support System of Retail Chain Assortment Management (DSS RAM).

The proposed algorithm targets the recommendation engine domain, specifically aiming to automate the process of order completion for retail purchases. Additionally, it facilitates the generation of documents related to goods distribution within the retail network. Our algorithm considers resource limitations (both commodities and store space) while enhancing Return on Investment (ROI) in commodity stocks. We acknowledge that technical and managerial constraints exist but simplify the algorithm for practical implementation. Our study mainly focuses on retail chains dealing with homogeneous products. While this simplification allows for clearer insights, we recognize that diverse assortments pose additional challenges. Such challenges require additional mathematical apparatus to navigate a dynamic landscape, leveraging data-driven strategies to optimize assortments and thrive in an ever-evolving market The interplay between consumer behavior, supply chain dynamics, and economic forces necessitates a holistic approach one that combines theoretical insights with practical solutions.

2. Literature review

Optimizing the assortment and providing stores with the most profitable products is challenging due to the many transactions involved in assortment management in the retail chain. Operational error monitoring is necessary and can only be implemented through an automatic decision support system (Dharmawardane et al., 2021). Shelby and Miller (1999) used a nonparametric approach to assortment optimization, but it is not applicable in large retail chains or for automation. Therefore, specific parameters for automated DSS RAM are needed.

Each store in the retail chain has its characteristics, such as trade margin, which may significantly differ for the same product in different stores due to regional and country price differences, tax, and competition levels (Borraz et al., 2024).

The warehousing costs remained outside our consideration since such costs do not significantly differ between stock-keeping units (SKUs) of a homogeneous product range. In the operation of retail chains, the analysis of commodity turnover assumes a central role. This analysis is conducted for each product within every store while considering store-specific trade margins.

In the context of our study, we exclude transport costs from consideration (except for cases involving goods redistribution between stores). Supplying goods to stores from Distribution Centers (DCs) occurs regularly. Routes are strategically planned to optimize transportation costs and ensure consistent replenishment and supply of a new assortment. Consequently, we do not employ spatial analytics to investigate demand variability and yield benefits (as discussed by Zhang and Nault (2024).

Furthermore, we exclude warehousing costs from our analysis, as those costs do not exhibit significant variation across SKUs within a homogeneous product range. In the operational context of retail chains, the analysis of commodity turnover assumes paramount importance, particularly concerning store-specific trade margins.

The literature review has delineated two primary approaches to assortment management: traditional and multipurpose. The latter is further categorized into various problem-solving types. These approaches address critical challenges, such as resource constraints, product quantity limitations, and the expanding assortment size. These constraints were incorporated as limits when constructing the assortment management model (see Table 1).

The traditional approach focuses on specific tasks aimed at increasing profit and trade income, whereas the multipurpose approach encompasses a broader range of objectives. Consequently, the key distinction lies in the number of indicators employed for problem-solving and the extent to which these indicators have been refined. Among the most prevalent constraints is the limitation on goods, with easily measurable quantitative characteristics. This constraint is typically based on consumer demand and inventory stock levels. The models developed in this context rely on statistical data predictions, especially when defining parameters that significantly impact sales volume for individual items (Hübner et al., 2016a, 2016b; Fildes et al., 2019; Ma et al., 2018; Huang et al., 2023). However, only a limited number of authors have explored the distribution of commodities in retail networks under scenarios characterized by stringent goods limitations (Fildes et al., 2021).

The multipurpose approach imposes limits on goods from each supplier, which results in a limited number of available goods in the market Economic models of the multipurpose approach do not aim to maximize profit. Resource limits are the most common type of limitation, including staff and cost limits (Muñoz et al., 2022). Cost-effectiveness is used as an indicator in retail management. However, defining characteristics for selected factors can be challenging, especially with an increasing assortment size.

Usually, the traditional approach maximizes the company's profit or income by increasing the assortment size (Holmström, 1998; van Woensel et al., 2007; Kök & Fisher, 2007; Xin et al., 2009; Yücel et al., 2009; Honhon & Seshadri, 2013; Hübner et al., 2013; Kök et al., 2015; Çömez-Dolgan et al., 2022). Some authors consider substitutes for traded goods (Ala-Risku et al., 2010; Honhon & Seshadri, 2013; Hense et al., 2022; Rooderkerk & Kök, 2019; Fisher & Vaidyanathan, 2014; van Donselaar et al., 2021).

The Multipurpose approach to increasing assortment size examines potential profits by balancing the costs associated with unfulfilled customer requests (shortage costs) against the liquidation value of unsold products (Hübner & Schaal, 2017). However, defining distinct parameters for each product within a retail chain containing hundreds of thousands of items present a challenging task (Hübner, 2017).

Table 1. Analysis of approaches to assortment management optimization

Main characteristics	Traditional approach	Multipurpose approach	Author's approach
Goal of approach	Increasing profit and trade income	Satisfying the customer needs and, as a result, increasing profit and trade income	Increasing profits
Improving delivery efficiency	By delivery time and cost (Eccles, 1991; Hunter et al.,1996; van Hoek, 1998; Kumar et al., 2020; Huang et al., 2023)	Based on comprehensive market analysis: customer needs, consumer value, market trends, competitors, suppliers, et al. (Nuttle et al., 1991; Dass & Kumar, 2012; Prem et al., 2017; Tan et al., 2024)	Ensures availability of products depending on profitability of selling of each product at each store
Resource limits	Company's internal resources (Kunz & Rupe, 1999; Bernstein et al., 2015; Muñoz et al., 2022; Chen et al., 2024; Gallego & Li, 2024)	Combining the resources of the company and suppliers (Hong et al., 2019; Bulava, 2020; Li & Gao, 2023; Zhang et al., 2024)	Combining the resources of the company and suppliers
Goods limits	Purchases is limited by consumer demand (Hübner et al., 2016a, 2016b; Ma et al., 2018; Fildes et al., 2019; Gallego et al., 2023)	Purchases have strong limitation by market and each supplier ("highseason", war) (Ala-Risku et al., 2010; Fildes et al., 2021; Yuzevych et al., 2023)	Purchases are limited by goods turnover, profitability of selling of each product at each store and stockout prevention
Increasing of assortment size	Depending on possible profit (Holmström, 1998; Kök & Fisher, 2007; Kök et al., 2015; van Woensel et al., 2007; Xin et al., 2009; Yücel et al., 2009; Hübner & Kuhn, 2012; Honhon & Seshadri, 2013; Çömez-Dolgan et al., 2022)	Satisfying the customer needs based on the number of substitutes (Honhon & Seshadri, 2013; Rooderkerk & Kök, 2019; Marshall & Ramnath, 2014; van Donselaar et al., 2021; Hense et al., 2022; Borraz et al., 2024)	Not included into the mathematical model, need human intervention
Automation possibilities	Does not provide for automation (Holmström, 1998; Kök & Fisher, 2007; van Woensel et al., 2007; Xin et al., 2009; Yücel et al., 2009; Hübner & Kuhn, 2012)	A set of guidelines requiring human intervention at various phases of product line management (Honhon & Seshadri, 2013; Rooderkerk & Kök, 2019; Marshall & Ramnath, 2014; van Donselaar et al., 2021; Hense et al., 2022; Basit et al., 2023; Javed et al., 2024)	Fully automated (Iurasov et al., 2021)

To achieve cost-effectiveness, it is recommended to implement a commodities management system based on real-time data regarding sales and inventories. Given relatively stable prices and minimal transportation costs, efficient distribution of commodity stocks from distribution centers (DCs) to stores and inter-store redistribution should prioritize maximizing the ROI in goods sold per day.

The proposed optimization approach also extends to inbound logistics. Rather than analyzing commodity turnover rates and overall trade margins separately for individual stores, this approach considers estimates across the entire retail chain. By aligning activities related to the physical distribution of goods throughout the retail chain, it maximizes the ROI in commodities. Therefore, the central focus of this article lies in assessing the return on investment for traded commodities.

Numerous algorithms and models exist for optimizing retail commodity flows. Some focus on reverse logistics processes (Aryee et al., 2024), while others target infrequently purchased goods like luxury goods, home appliances, and furniture (Miller et al., 2010). Additionally, some are oriented toward optimizing the supply chain in retail network, identifying demand and supply chain planning issues, and proposing opportunities for further research, such as creating Decision Support Systems (DSS) for demand prediction and assortment optimization. (Gallego & Li, 2024).

However, this paper focuses on developing a practical algorithm tailored to commonly purchased goods, where client choice significantly impacts sales. For example, consumers often repurchase products such as food and shoes in standard sizes. Existing apparel systems (Nuttle et al., 1991; Kunz & Rupe, 1999; Hunter et al., 1996) cannot be relied upon, as their algorithms are proprietary and cannot be upgraded. Therefore, we aim to create a new model to address this specific scenario.

Since the optimization algorithms "are limited in their practical application due to extensive data requirements, limitations in solving practice-relevant problem sizes or extensive programming requirements to implement sophisticated heuristics" (Hübner, 2017), the presented model is simplified and applicable without significant investments in equipment and staff training. For decision-support should be used existing data sets (available in any software of sales management). Calculation algorithms must be simple and provide high accuracy within time and equipment constraints.

Calculations should be based on real-time information for many items across the retail assortment. For example, when selling apparel, each unique combination of design, color, and size constitutes a separate element within the assortment. These calculations need to consider the extensive network of stores.

3. Methodology

Retail networks usually purchase products from manufacturers or large wholesalers, store them in company's DCs, and distribute them to stores. Traditionally, managing product flow within a retail chain requires significant manual labor (see Figure 1).

However, most optimization models are limited in practical application (Heger & Klein, 2024). Therefore, the presented model has been simplified for its application without significant investments in equipment or the need to update personnel qualifications. Existing datasets from any sales management software can be utilized for our DSS RAM.

The set of goods V represents complete inventories (all commodity assets of the enterprise) and is considered known. The problem of optimal distribution of V goods between Y stores is one of the primary tasks of retail assortment management in retail trade.

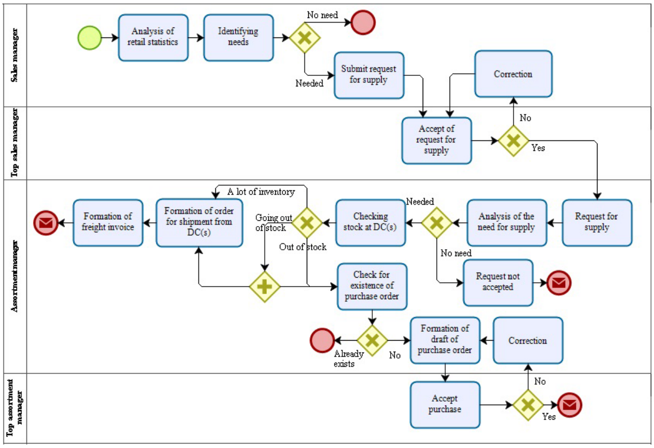

Figure 1. Traditional algorithm of assortment management

If the vector a_j from V is the part that will be given to the participant "j", it is necessary that:

$$V = a_0 + ... + a_Y = \sum_{j=0}^{Y} a_j . \tag{1}$$

Since $A = (a_0, ..., a_Y)$, it follows that a_j has M components, and component a_{ji} represents the quantity of the product "i" that participant "j" has (e.g., a store from the retail chain or DC).

The daily adjustments to trade margins in retail are unfeasible due to various technical constraints. Instead, the prices are periodically (for example monthly) reviewed, allowing for potential changes in trade margins during promotional events and sales periods.

The author's algorithm relies on the existing distribution route network, and in our presented model, delivery costs are minimized through economies of scale (Brakman et al., 2001).

The additional constraints relevant to assortment optimization encompass several factors. Firstly, there is the rational distribution of commodity stocks among stores. Secondly, the need arises to allocate expiring goods to areas with a higher likelihood of sales. It is crucial to ensure that expiring goods (such as grocery items or seasonal apparel assortments transitioning from winter to spring) do not surpass the mean sales level for the remaining days until their expiry date. Furthermore, a necessary inventory level directly tied to sales is specified in Equation (2). Even if a store typically sells less than one unit of each item until the next delivery, maintaining a minimum of one unit per item is deemed appropriate (Equation (3)):

$$1 \geq Sr_j \times \bar{S}_j^i; \tag{2}$$

$$1 < Sr_j \times \bar{S}_j^i, \tag{3}$$

where $\bar{S}_j^i$ – average sales of product "i" in-store "j"; Sr_j – inventory-to-sales ratio in a store "j".

In the next step, we calculate the coefficient of commodity turnover according to Iurasov et al. (2021):

$$T_j^i = \frac{\left(S_j^i - 2D_j^i - Ex_j^i\right)}{\left(G_j^i + In_j^i + Out_j^i\right)}, \tag{4}$$

where S_j^i – the quantity of product "i" sold per day through the store "j"; D_j^i – the quantity of defective product "i" returned per day to store "j"; Ex_j^i – the quantity of the product "i"

in the store "j" that is to be written off, due to the expiry date; G_j^i – the remnants of the product "i", at the beginning of the trading day, in the store "j"; In_j^i – the quantity of product "i" received per day in the store "j"; Out_j^i – the quantity of product "i" dispatched per day from the store "j" to DC(c) or other stores.

To measure daily ROI in SKU we calculate the coefficient of profitability by multiplying the daily coefficient of commodity turnover by the margin:

$$Pr_j^i = M_j^i \times T_j^i, \tag{5}$$

where Pr_j^i – coefficient of profitability of trading commodity "i" in the store "j"; M_j^i – trade margin for commodity "i" in the store "j".

To capture the evolving dynamics of the ROI in SKU, we establish a comprehensive profitability coefficient (Cpr_j^i). Cpr_j^i illustrates the trend in profitability, considering the temporal significance of its values (6). To account for their significance, various mathematical methods can be employed. In the simplest scenario, we utilize an arithmetic progression with multipliers (M_0) and (M_1). The sum of these multipliers should equate to 1. Hence, the calculation of the consolidated coefficient of profitability takes an autoregressive form:

$$^{first}Cpr_j^i = \mathrm{Pr}^i{}_j; \quad ^{cur}Cpr_j^i = {}^{prev}Cpr_j^i \times M_1 + \mathrm{Pr}^i{}_j \times M_0, \tag{6}$$

where $^{first}Cpr_j^i$ – the consolidated coefficient of profitability of the first day of trade of commodity "i" in the store "j" (it is assumed that previously we did not sell such product in the store); $^{cur}Cpr_j^i$ – the consolidated coefficient of profitability of the last (current) day of trade of commodity "i" in the store "j"; $^{prev}Cpr_j^i$ – the consolidated factor of profitability of the penultimate day of trade of commodity "i" in the store "j".

Within the DSS RAM, Cpr_j^i serves as the primary focus of analysis.

The self-regulating mechanism of the system for optimizing retail: a decrease in the quantity of product inventories increases the coefficients for commodity turnover (T_j^i), profitability, as well as the comprehensive profitability coefficient (Cpr_j^i) for each product.

Now we need to create the algorithm for purchasing goods in the retail network. It is not enough to use Cpr_j^i, we need to compare the Cpr_j^i, considering the sales volumes of each store. To this end, the Cpr_j^i multiplied by the coefficient of participation of the store in the company's total sales.

The participation coefficient of a store in the total volume of the company's sales is determined by calculating the ratio of the commodity's sales volume through that specific store for the study period to the overall volume of commodity sales across the entire retail chain.

$$Ki_j = S_j^i / S_{total}^i, \tag{7}$$

where Ki_j – coefficient of participation of store "j", in the total sales of product "i", S_j^i – product "i" sales in store "j", S_{total}^i – total product "i" sales throughout the retail network.

Summing up, for each commodity, the multiplication of the Cpr_j^i and the coefficient of participation of the store in the total volume of sales, we will obtain comparable summary indicators of profitability from selling various commodities throughout the retail network.

$$Cpr^i = \sum_{j=0}^{l} (Ki_j \times Cpr_j^i), \tag{8}$$

where Cpr^i – the comprehensive profitability coefficient for product "i" throughout the retail chain.

Now, the remaining task is to allocate the investment amount for purchasing commodities among different commodity categories. Priority should be given to the most profitable items (those with the highest coefficient values), while reducing or eliminating funding for items with profitability lower than the specified threshold.

A similar approach can be applied to correlate the profitability of various stores. This can be useful when deciding whether to liquidate the least profitable stores or develop the most profitable ones. For this purpose, it is necessary to calculate the participation rate of product "*i*" in total sales of store "*j*".

$$Kj^{i} = S_j^i \,/\, S_j^{total}, \tag{9}$$

where Kj^i – coefficient of participation of product "*i*", in the total sales of store "*j*"; S_j^{total} – total sales throughout the store "*j*".

The sums of these coefficients multiplied by Cpr_j^i will provide comparable summary indicators of the profitability of sales across various stores:

$$Cpr_j = \sum_{i=0}^{m} (Kj_i \times C), \tag{10}$$

where Cpr_j – comprehensive trade profitability coefficient of the store "*j*".

Based on the data received, investments should be allocated to the most profitable stores according to the priority rule, giving precedence to stores with larger coefficient values.

The structure of the algorithms of DSS RAM is shown in Figure 2.

The information regarding trading margins, sales volume dynamics, and trade balances (as input into the analysis system) is transformed into the variable Cpr^i_j. Together with data on the inventory levels of distribution centers (DCs) and retail shops, this information informs commodity distribution decision-making.

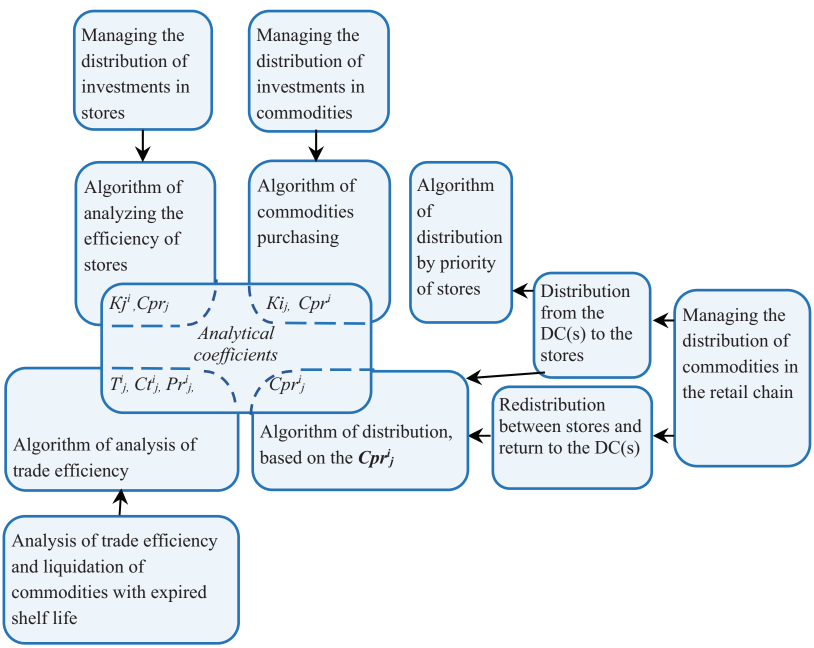

Figure 2. Structure of the algorithms for optimizing the assortment management

The DSS RAM automatically creates drafts of bills of lading and orders for the purchase of goods.

In a situation where it is necessary to expedite the sale of goods with an expiring shelf life, according to the algorithm, the products are assigned to locations where it can be sold the fastest, rather than where it yields the greatest profit.

The algorithm for moving goods between stores is similar. However, instead of considering the full resources, it analyzes the commodity stocks in stores for redistribution. In addition, the value of the Cpr_j^i for a given product in one store exceeding the value of a similar coefficient in another store does not necessarily imply that the commodity should be moved between stores. This is to avoid extensive, sometimes cyclical, flows of small quantities of goods (e.g., one or two pairs of shoes) between stores. Therefore, two criteria should be included in the analysis:

the threshold for the coefficient of consolidated profitability to move goods from one store to another (Equation (11)), for example, exceeding more than twice should ensure that we do not have to return this product later;

the presence of regular transport links between the source and the recipient. It is not mandatory that transporting cargo between stores should be combined with the planned delivery of the goods from the DCs (the truck visits in turn both stores); goods can be transferred to a DC for subsequent shipment to another store.

These criteria are not absolute and depend on the specific circumstances of the firm and require "verification" (the search for the most optimal value, in practice). After implementation, they need to be reviewed and adjusted according to changes in market conditions.

For example, an additional condition is introduced:

$$Cpr^i_{receiver} > Cpr^i_{source} \times Kr,\ i = (0, \ldots, m), \tag{11}$$

where $Cpr^i_{receiver}$ – comprehensive trade profitability coefficient of product "*i*" by store, serving as the final destination of the movement of the commodity; Cpr^i_{source} – comprehensive trade profitability coefficient of product "*i*" by store, serving as the starting point of the movement of the commodity; Kr – coefficient reflecting the significance of exceeding the value of the comprehensive trade profitability coefficient in one store over the coefficient of another.

When redistributing commodities with expiring shelf life (or during assortment changes for a different season), the vector of total resources will consist of such commodities. These commodities are analyzed for redistribution to stores with higher turnover:

$$Ct^i_{receiver} > Ct^i_{source} \times Kex,\ i = (0, \ldots, m), \tag{12}$$

where $Ct^i_{receiver}$ – comprehensive coefficient of commodity turnover of commodity "*i*" by store, serving as the final destination of the movement of the commodity; Ct^i_{source} – the consolidated coefficient of commodity turnover of commodity "*i*" in the store, serving as the starting point of the movement of the commodity; Kex – coefficient reflecting the significance of exceeding the value of the consolidated turnover ratio of product "*i*" in one store over the same coefficient of the other store, e.g., exceeding by 1.5 times (by 50%).

A real dataset was employed to assess the efficacy of the algorithm under consideration.

4. Results

We investigated the retail strategies using a real-world retail dataset that includes multiple stores and products, to evaluate the effectiveness of the proposed decision support algorithm. The dataset originated from a physical apparel chain and was initially recorded in the form of orders. Sales quantities for each item across various stores were captured from these orders and saved in real-time within the database. Specifically, this sales dataset covers 100 different products across 20 stores located in 5 regions of Ukraine. The temporal span of the data ranges from 2021 to 2023, resulting in a total of 1,119,837 data entries. After data cleaning, the final dataset comprises 982,538 data entries, each representing a unique data point.

In this study, we utilized data from the year 2021 as our dataset for the efficiency algorithm evaluation. The dataset comprises a total of 392,512 data entries. During the training phase, we collected data from a set of stores and items at each step, aggregating them into a matrix that represents item sales across various stores. Also, we calculate mean values for sales data related to identical items across different time steps within each store for the year 2021. Table 2 illustrates the heterogeneity of sales data grouped by region.

Table 2. Summary statistics of sales data by region

	Region 1	Region 2	Region 3	Region 4	Region 5
mean	155.98	168.38	354.64	161.99	182.93
std	29.63	32.61	41.63	25.54	38.54
min	116.84	130.71	195.87	121.72	135.14
max	286.42	321.02	488.55	304.76	332.49

We investigate the retail strategies employed in each store for each product. We analyze the differences in trade margin and its impact on commodity turnover and profitability. The difference in trade margin for the product is illustrated in Table 3.

Table 3. Descriptive statistics of the trade margin by region

	Region 1	Region 2	Region 3	Region 4	Region 5
mean	46.44	52.67	66.05	63.48	70.74
std	16.86	17.32	17.01	18.38	19.13
min	38.33	39.43	52.98	40.21	42.24
max	71.16	80.21	93.34	84.72	88.51

Table 4 displays the dynamics of changes in turnover and profitability coefficients over an 12-months interval retail establishments by region. It should be noted that the first period in the Table 3 is not the date of start of trade in this commodity. Notably, stores with low trade margins demonstrate higher turnover compared to stores with high trade margins. This suggests that price leadership strategies adopted by stores can lead to increases in both turnover and profitability, despite lower retail margins.

The stores with higher trade margins recorded higher profitability compared to the stores with lower trade margins. However, the study indicates that the profit margin alone does not fully determine the overall profitability of a retail strategy. Factors like commodity turnover and the price sensitivity of customers play significant roles. If the price level is lower, each pair of shoes brings a smaller amount of trade margin to the company's budget. This raises the question: which of the two options should be considered more. Also, trade margins are higher in central stores in big cities compared to stores in towns or non-central areas. Trade margins in large cities are higher than in towns.

Table 4. Dynamics of key performance indicators of apparel chain by region (as a percentage in the same period of the previous year)

Month	Region 1			Region 2			Region 3			Region 4			Region 5		
	T	Pr	Profitabily	T	Pr	Profitabily	T	Pr	Profitabily	T	Pr	Profitabily	T	Pr	Profitabily
1	0.83	0.83	1.31	0.85	0.39	1.12	1.06	1.18	3.32	0.83	0.81	1.24	1.21	0.49	1.28
2	0.91	0.76	1.27	0.93	0.45	1.04	1.25	0.98	3.18	0.91	0.88	1.17	1.14	0.46	1.21
3	0.9	0.77	1.3	0.92	0.48	1.24	1.15	1.03	3.41	0.90	0.87	1.26	1.22	0.50	1.30
4	1.07	0.64	1.24	1.09	0.51	1.04	1.36	1.12	3.47	1.07	1.04	1.26	1.22	0.49	1.30
5	0.85	0.61	1.15	0.87	0.45	1.13	1.09	1.08	2.76	0.85	0.83	1.25	1.22	0.49	1.29
6	0.93	0.58	1.17	0.95	0.47	1.25	1.19	0.97	3.29	0.93	0.90	1.18	1.14	0.46	1.22
7	0.91	0.55	1.15	0.93	0.52	1.26	1.16	0.99	3.14	0.91	0.88	1.19	1.15	0.47	1.22
8	1.19	0.52	1.33	1.21	0.5	1.17	1.45	1.03	2.78	1.19	1.15	1.29	1.25	0.51	1.33
9	1.07	0.49	1.23	1.09	0.45	1.15	1.36	1.09	3.24	1.07	1.04	1.27	1.24	0.50	1.31
10	0.95	0.53	1.18	0.97	0.53	1.15	1.21	1.17	3.19	0.95	0.92	1.17	1.14	0.46	1.21
11	0.83	0.56	1.19	0.85	0.52	1.04	1.06	1.10	3.2	0.83	0.81	1.17	1.13	0.46	1.20
12	1.13	0.87	1.24	1.15	0.53	1.04	1.44	1.12	3.25	1.13	1.09	1.16	1.13	0.46	1.20
Ave-rage	0.96	0.64	1.23	0.98	0.48	1.14	1.23	1.07	3.19	0.96	0.94	1.22	1.18	0.48	1.26

First month Cpr_j^i of each product is significantly different which means that trading this product is almost 1.5 times more profitable in Region 3, than in Region 2.

However, the price leadership strategy chosen by Region 3 starts to bear profits and commodity turnover in Region 2 (where the population has lower income than in Region 3) became significantly higher than in the Region 3. This leads to an increase in the coefficients of profitability.

The described algorithm was introduced into the operation management of a chain of clothing stores and all results got from real data after changes.

Algorithms of DSS RAM allow us to consider the changes in characteristics of the commodity turnover and profitability through the mechanism of consolidated coefficients.

Below are statistical data for 4 stores in one region using the example of one product. This will allow you to show changes in odds and profits clearly. Below are statistical data for 5 regions using the example of one product. This will allow you to show changes in odds and profits clearly. From all coefficients, a more preferred situation in store with high trade margin in Region 3 (coefficient value: 1.34), the increase in commodity turnover compensates for stores with a lower trade margin in Region 1 (coefficient value: 0.986). The stores in Region 4 have a preferable dynamic of sales of commodity stocks (for this assortment position) multiplied by the trade margin.

The algorithm proposed in the article and implemented in the apparel chain showed its effectiveness and the changes made increased the company's profit from 1.14% (Region 2) to 3.19% (Region 3).

Consequently, the DSS RAM dispatches the flow of goods to the shop (in the case of inbound logistics to the company). This results in higher inventory levels and lower turnover, consolidated turnover, profitability and consolidated profitability ratios.

In turn, the fall in the coefficients signals the DSS RAM the need to reduce the volumes of supply of goods or to completely stop deliveries and purchase other, more profitable goods (see Figure 3).

The findings of this study highlight the complex interaction between pricing strategy, trade margin, commodity turnover, and profitability. Although the stores in the central part of cities achieved higher profits due to their higher trade margin, the stores with low trade margins were able to attract more customers with their lower prices, leading to increased commodity turnover and overall profitability.

Figure 3 illustrates the application of the DSS RAM algorithms.

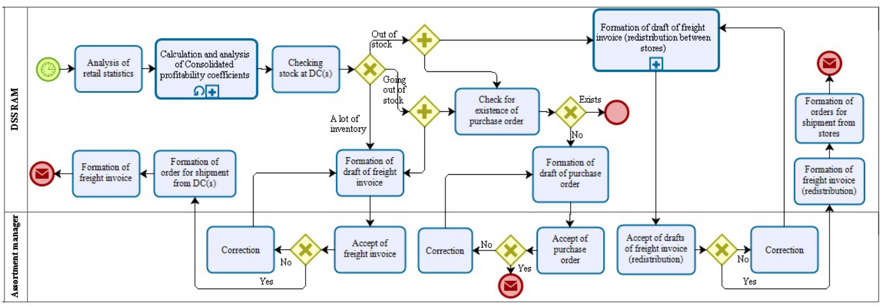

Figure 3. Algorithm of DSS RAM

In conclusion, this demonstrates that a pricing strategy with a lower trade margin, such as that adopted by the "Atmosphere" store, can result in higher commodity turnover and increased profitability, even compared to a strategy with a higher trade margin such as "Central Mall". The DSS RAM works on the idea of autoregulation, where reducing trade inventory increases commodity turnover and profitability ratio, which leads to a higher inventory level.

Retail activities in the distribution chain are driven by the goal of maximizing profits from capital investments. After the algorithm implementation, the average profitability growth for the apparel chain is 1.61%.

The presented DSS RAM algorithms are applicable for homogeneous product ranges and impose no need for considerable investments in equipment and updating of personnel qualifications. The automatic drafting of waybills, invoices, shipment documents from DCs and stores, and requests for supply of products is only a special case of application of DSS RAM. The introduced theoretical framework optimizes decision-making in assortment management to achieve higher ROI in SKU.

5. Discussion

The study's primary findings indicate that the commodity turnover coefficient (Equation (4)) and the margin rate jointly influence the profitability rate (Equation (5)). By employing a comprehensive coefficient for commodity turnover, researchers were able to track product demand not only daily but also over extended sales periods. This approach provided valuable insights into profitability trends.

The DSS RAM, based on the proposed model, has been demonstrated its effectiveness in optimizing retail operations. By automatically generating draft bills of lading and purchase orders for goods, the DSS RAM facilitates a more streamlined and cost-effective distribution of commodities throughout the retail chain. Moreover, the simplified algorithm, relying on existing data sets and simple but efficient calculation algorithms, ensures applicability without significant investments in equipment or staff development.

It is crucial to highlight that while the proposed algorithm significantly increased the profitability of investments in goods and facilitated better resource and shelf space management, it cannot entirely replace human input. Human control remains essential to oversee the formation of coefficients and make strategic decisions. Moreover, automated systems cannot account for various unregulated factors affecting retail operations. Therefore, the ability to manually adjust the DSS RAM coefficients is vital to cater to the complexities of individual stores and the entire retail chain.

Further research may provide solutions to a few of the following issues:

- Category management practices, such as those described by Hamister and Fortsch (2016), can be useful for both individual stores and entire retail chains. These practices may be required to manually adjust DSS RAM in anticipation of changes in customer demand and to take preventive actions to respond to those changes. These practices enhance the adaptability of retail chains to dynamic market conditions and reinforce the importance of human oversight in decision-making processes (Sillanpää & Liesiö, 2018).
- Integration of Pricing Analytics: Future research can focus on integrating advanced pricing analytics techniques into the proposed model to further optimize pricing strategies in the retail chain. This can involve leveraging data science and machine learning algorithms to analyze customer behavior, preferences, and purchase patterns to determine optimal price for different products (Peng et al., 2024).
- Value-Based Pricing Optimization: researchers can explore the application of value-based pricing optimization techniques, where prices are set based on the perceived value of products to customers. This approach can help retailers align prices with customer expectations, leading to increased turnover and sales (Xu & Wang, 2018)
- Machine Learning for Demand Forecasting: Utilizing machine learning algorithms, such as time series forecasting and demand prediction models, can enhance the accuracy of demand forecasting for different products. Improved forecasting can aid retailers in managing inventory and meeting customer demands, ultimately leading to increased turnover (Dharmawardane et al., 2021).
- Integration of Linear Regression: Linear regression can be integrated into the model to understand the relationship between pricing and turnover/sales. This can help retailers identify the pricing ranges that maximize turnover and profitability for various products (Aouad et al., 2023).
- Multi-Objective Optimization: Researchers can explore multi-objective optimization techniques that consider both turnover and profitability simultaneously. This approach can help retailers strike a balance between maximizing turnover and maintaining profit margins, leading to more informed pricing decisions (Kumar et al., 2019; van Donselaar et al., 2021; Schäfer et al., 2022).

By combining the DSS RAM with cutting-edge data science and pricing analytics tools, future research can unlock new possibilities for retailers to optimize pricing strategies and achieve greater turnover and sales in the retail chain. These advancements can lead to a more efficient and customer-centric retail industry that maximizes profits while meeting the needs and preferences of consumers.

6. Conclusions

The economic processes involved in retail decision-making are highly complex, making it impossible for computer systems to completely replace human input. As such, periodic human control is necessary to oversee the key performance indicators and to make strategic decisions. However, the proposed algorithm for the Decision Support System of Retail Chain Assortment Management (DSS RAM) minimizes human input to the assortment optimization by using available resources. The DSS RAM forms the product assortment based on costs, and margins, and time limitations.

The proposed algorithm increases the profitability of investments in goods considering the restrictions on inventory and capacity of stores. The apparel chain has shown a growth in average profitability, with an increase of 1.61%. This improvement in profitability reflects the created algorithm's ability to optimize inventory and assortment.

The average commodity turnover for the apparel chain rose by 1.07%. This indicates that the commodity is distributed more efficiently through the supply chain, increasing sales and turnover.

Specifically focusing on average commodity turnover by margin, there was a 0.72% average increase.

This suggests that the company not only increased sales volume but also maintained or improved profit margins on those sales.

In summary, the apparel chain achieved positive growth in profitability after using the DSS RAM algorithm, saw an increase in commodity turnover, and managed to improve margins on its turnover. These indicate economic efficiency for the proposed algorithm.

Simplifying the algorithm eliminates the number of technical and managerial constraints on implementation but limits its application. Therefore, the findings of this study have to be seen in light of some limitations:

- limited scope of analysis and applicability of algorithms (only for retail chains of homogeneous products),
- the use of simple algebraic operations instead of artificial intelligence methods,
- changes in trade margins are not included in the model being developed; this may serve as the subject of further research.

This research study fills the knowledge gap by creating a theoretical algorithm for optimizing the assortment and maximizing the profitability of retail stores. In practice, this scientific knowledge addresses the challenging task of maximizing the profitability of retail stores through efficient assortment management across the retail chain. The study focuses on developing a practical model tailored to frequently purchased products, where consumer preferences significantly impact sales, such as food items and footwear.

The study emphasizes the importance of real-time sales and stock data for establishing an effective inventory maintenance system that manages commodity stocks. Valuable insights into product demand and profitability trends are gained by utilizing consolidated coefficients of commodity turnover and profitability (as expressed in Equations (4), (5), (6), (8), and (10)). This comprehensive analysis, spanning the entire retail chain rather than individual stores, provides a holistic understanding of inventory management effectiveness.

It is crucial to recognize the indispensable role of human oversight in forming these coefficients and making strategic decisions. While the proposed algorithm significantly, directly addressing the scientific knowledge gap enhances, profitability and resource management, automated systems cannot fully account for various unregulated factors that may impact retail operations. Therefore, the ability to manually adjust the Decision Support System for Retail Chain Assortment Management remains essential to address individual store complexities and adapt to dynamic market conditions.

The study introduces a model for optimizing commodity flows within the retail sector, focusing on frequently purchased products. By integrating human expertise with automated decision support, the proposed algorithm enhances profitability and efficiency in retail chains. The presented model serves as a valuable foundation for future research and enhancements in retail optimization strategies, ultimately advancing the field of retail management toward more profitable and customer-centric operations.

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