Conceptual Framework for a Multidimensional Index for Evaluating the In-store Operational Performance Within Retail Chains

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Abstract: The current paper presents a conceptual framework for developing a multidimensional index designed to assess the operational performance of retail chains. Traditional tools such as Key Performance Indicators (KPIs), the Balanced Scorecard, Data Envelopment Analysis (DEA), and the Altman Z-score provide only partial insights and lack comprehensive integration of financial, operational, behavioral, and external dimensions for the organization. The proposed index addresses this gap by combining a wide range of internal and external indicators, including sales potential, staff efficiency, customer behavior, inventory management, financial sustainability, and location-related factors.

The methodology incorporates various statistical and analytical methods to ensure statistical validity. This framework supports comparative analysis, predictive modeling, and the evaluation of targeted interventions. By integrating big data analysis techniques and machine learning, the index serves as a scalable and adaptive management tool, aiding in the development of strategic decisions within dynamic retail environments.

Keywords: multidimensional index, retail performance, discriminant analysis

JEL: M10, M11, M21

1. INTRODUCTION

The proliferation of multidimensional primary and secondary data sources enhances the methodological capabilities for conducting multivariate analyses of physical retail outlet performance within complex retail ecosystems. The increasing data collateral facilitates a comprehensive re-examination of prevailing performance monitoring methodologies and supports the development of advanced analytical frameworks grounded in empirical evidence and statistical rigor.

The dynamic and highly competitive nature of contemporary retail environments necessitates the design of a robust and adaptable performance measurement tool that integrates financial indicators with operational metrics, product turnover rates, customer engagement factors, and physical characteristics of the retail space. The proposed concept of a multidimensional integrated index seeks to enhance the current methodological toolkit for the quantitative assessment of retail operations across nationally presented outlet networks.

The index design process is grounded in the identification and determination of a comprehensive set of predefined criteria, encompassing both static and dynamic performance dimensions. These criteria are subjected to statistical validation, including correlation analysis, factor reduction techniques, and weighting procedures to ensure that the final index structure balances indicator relevance with statistical significance. This enables analysis and comparative assessment at multiple levels, including retail-specific, regional, and cluster-based groupings.

The proposed concept integrates quantitative metrics, capturing commercial productivity, operational efficiency, local market dynamics, and exogenous environmental variables. Through the systematic construction of a validated indicator set, the index offers a versatile and scalable framework for interpreting complex retail performance data. It supports benchmarking, monitoring, and predictive modeling, thereby contributing to both operational decision-making and strategic retail planning.

Furthermore, the integration of normalization, standardization and data aggregation techniques enhances the interpretability and comparability of the resulting index. This ensures its usability in high-volume data contexts where dimensionality reduction and noise filtering are critical for obtaining actionable insights. The index serves not only as a diagnostic instrument for operational oversight but also as a foundational tool for machine-learning-based forecasting models, cluster analysis, and performance optimization initiatives across large-scale retail networks.

2. REVIEW OF THE CLASSICAL APPROACHES

2.1. Key performance indicators (KPIs)

Key Performance Indicators (KPIs) are quantitative measures used to systematically evaluate the effectiveness and efficiency of retail operations. They are essential tools for monitoring performance, identifying trends over time, and supporting data-driven strategic decisions. KPIs enhance the assessment of sales performance, customer behavior, inventory management, and overall operational success. These tools are crucial for helping businesses achieve their predetermined goals and maintain a competitive advantage in dynamic markets.

Key Performance Indicators (KPIs) offer organizations a reliable set of information that serves as a foundation for implementing growth strategies. These indicators reveal the strategic significance of planned actions and their impact on promoting desired behaviors. The primary goal of using KPIs is to enhance operational efficiency, productivity, and profitability [1].

Key Performance Indicators (KPIs) are considered improvements at both strategic and operational levels. Through a series of actions, they provide an analytical framework for developing solutions and enhancing knowledge [2].

A crucial aspect of utilizing a performance measurement system based on key indicators (KPI) is identifying a comprehensive set of performance indicators that thoroughly examine the main processes. These indicators can be categorized into two primary groups:

financial (or cost-based) performance indicators and non-financial performance indicators [3].

In addition to the main groups of indicators previously discussed, various industries have specific indicators that are essential for measuring performance. Key elements include customer satisfaction, product quality, supply reliability, employee-related factors, productivity, financial outcomes, safety, employee satisfaction, community, and environmental concerns, etc.

Depending on the particular characteristics of the economic sector being examined and the unique attributes of a specific company, different sets of measures can be utilized to assess efficiency [4]. These measures evaluate an organization's efficiency by breaking down the entire business into individual processes.

2.2. Balanced scorecard

Balanced Scorecard (BSC) is a framework for evaluating a company that goes beyond financial performance to also consider the company's success in satisfying customers, operating efficiently, and innovating for the future [5, 26, 27].

In the literature, assessment systems can be categorized into several subtypes, including balanced scorecard systems and credit scorecard systems, among others. The balanced scorecard is a strategic performance management tool that helps identify and improve various internal business functions and their resulting external outcomes [6, 26, 27].

The balanced scorecard provides a data-driven framework to analyze performance across four key dimensions. Financial metrics such as sales revenue growth, profit margins, inventory turnover, and average transaction value are combined with customer-focused indicators like satisfaction scores, foot traffic, and retention rates [7].

The indicators related to internal processes—such as stockout rates, order fulfillment times, and process compliance—identify bottlenecks and optimize supply chains. Additionally, learning and growth metrics, including employee turnover, training hours, and innovation activities, are monitored to ensure long-term operational resilience and capability development.

By applying the balanced scorecard model, organizations can integrate both quantitative and qualitative indicators, providing a comprehensive view of overall performance. Analysis may include correlation models between customer and internal process perspectives and their impact on financial outcomes. This approach allows for the identification of causal relationships beyond surface-level results, thereby supporting machine learning initiatives, resource allocation, and the adjustment of strategic objectives to facilitate continuous improvement [8].

2.3. Data envelopment analysis (DEA)

Data Envelopment Analysis (DEA) is a non-parametric technique used to evaluate the operational efficiency of decision-making units (DMUs) such as companies, universities, or hospitals. The input-oriented DEA model can be formulated as a linear programming problem, where the objective is to minimize a scalar efficiency score θ. The primary goal of DEA is to compare multiple entities that convert similar inputs into outputs to identify an efficient frontier. DMUs that operate below this frontier are considered inefficient [9].

Minimize θ

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \Theta_{x_{i0}} ; i = 1, \dots, m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{r0} ; r = 1, \dots, s$$

$$\lambda_j \geq 0; j = 1, \dots, n$$

Where:

θ- represents the efficiency score of the DMU

λ_j - eights assigned to peer DMUs

An efficiency score θ=1 indicates that the DMU is efficient, while θ<1 implies that it can proportionally reduce input without decreasing output.

The considered approach to performance analysis is applicable in several areas, including performance analysis in the retail sector [11], information security and processes [12], logistics [13], etc.

The methodological framework of DEA is based on a model that employs mathematical linear programming for each DMU being analyzed. The essential steps of this framework include:

- Assigning weights to inputs and outputs to maximize the relative efficiency score of each unit.
- Solving a fractional programming problem that optimizes the ratio of weighted outputs to weighted inputs.
- Repeating the process for all DMUs to determine the efficiency frontier.
- Employing either an input-oriented approach, which minimizes inputs for a given output, or an output-oriented approach, which maximizes outputs for given inputs.

Popular models within DEA include the CCR model [9], which assumes constant returns to scale, and the BCC model [10], which allows for variable returns to scale.

The main advantages of DEA include:

- No requirement for a predefined production function.
- The capability to manage multiple inputs and outputs simultaneously.
- The ability to identify sources and levels of inefficiency for each unit.
- Its usefulness for benchmarking and recognizing best practices.

At the same time, there are a number of limitations linked to this approach , such as:

- High sensitivity to data quality and the presence of outliers.

- Inability to distinguish between noise and inefficiency.
- Lack of accounting for statistical noise.
- Efficiency scores are relative only to the sampled units.
- A large number of inputs and outputs can result in inflated efficiency claims.

2.4. Altman z-score

Altman's Z-score model is a quantitative tool designed to predict the risk of corporate bankruptcy using multivariate discriminant analysis (MDA). The model combines several financial ratios into a single score to differentiate between solvent and insolvent firms [14].

The methodology employs MDA to determine optimal linear coefficients aimed at maximizing the separation between groups by minimizing intra-group variance and maximizing inter-group distance. Altman evaluated twenty-two financial ratios and selected five key predictors that represent liquidity, profitability, leverage, solvency, and efficiency.

The weights assigned to the variables are derived from the discriminant function, reflecting each ratio's predictive power within the sample space. The Z-score can be adjusted for non-manufacturing contexts, private firms, or international applications, necessitating the re-estimation of coefficients and potential modifications of input variables [15].

This flexibility makes the Z-score method an example of robust predictive modeling, relevant to modern systems that rely on data-driven analytics. Thus, the model illustrates how discriminant analysis can convert financial statement data into actionable probabilities of default across various industry conditions.

The adaptability of this methodology allows it to be applied in a wide range of situations and industries. Numerous examples of the adaptation of the Altman model can be found in the literature, covering sectors such as manufacturing [16] and mining [17], among others.

The Altman model is designed to assess potential bankruptcy risks from the perspective of the specific company being analyzed. The methodology used to develop this model allows for modifications to the original concept, enabling it to be utilized as a tool for evaluating the performance of retail outlets.

The approaches mentioned often fail to provide a coherent and objective comparison of business units within the fast-moving consumer goods sector. Although they each have their merits, existing tools do not form an integrated and consistent index that offers transparent and actionable insights for benchmarking retail outlets in a large chain.

To fill this gap, there is a clear need for a scientifically validated composite performance index that combines multiple indicators. This index would facilitate objective comparisons between units, thereby supporting evidence-based management and strategic decision-making in the retail sector.

3. CONCEPTUAL FRAMEWORK

3.1. The essence of the problem

The dynamic and highly competitive nature of the modern retail reality reveals the need to develop a reliable and adaptable performance monitoring tool that integrates a set of indicators, including financial, operational metrics, stock rotation, customer engagement, and physical characteristics of the retail space. A conceptually new solution based on a multidimensional integrated index is proposed, which aims to improve the current methodological toolkit for quantitative assessment of commercial operations in nationally represented commercial networks.

With the increasing availability of data based on in-store sensors, transactional systems, CRM tools, and market intelligence platforms, retailers are faced with the challenge to address not only larger volumes of data but also more complex, multi-source, and multidimensional data.

However, existing performance observing methodologies often remain siloed, rigid, and unidimensional. They tend to focus solely on sales or operational efficiency, failing to capture the interactions between financial, behavioral, spatial, and contextual drivers.

The proposed approach introduces a multi-factor aggregate indicator designed to systematize and integrate a diverse range of quantitative data related to the commercial activities of physical retail outlets in the FMCG (fast-moving consumer goods) sector.

This index serves as a unified tool for comparative analysis, reflecting the internal operational state of the store while also incorporating external factors that pertain to the socio-economic environment, territorial structure, location, and competitive landscape. The concept functions as an indicator of the current state of the stores analyzed, based on objective, and regularly updated empirical data.

A pivotal feature of this index is its multidimensional nature and its potential for full integration into various processes. It goes beyond merely considering internal operational data to systematically include external parameters that reflect territorial specifics, demographic characteristics, and the broader economic conditions. The initial set of indicators offers a comprehensive view of the environment impacting performance.

Unlike traditional assessment methods that focus solely on financial results, this approach establishes a more complete foundation for objective comparative analysis, the identification of underlying connections, and the formulation of effective management strategies. The process aims to create a tool that allows for the continuous monitoring of a set of aggregated indicators reported through a common index. Regular updates are justified by the dynamics of trade in fast-moving goods, where consumer behavior can change rapidly and seasonal fluctuations are common. Regular oversight enables timely management responses.

Monthly monitoring enhances the sensitivity and flexibility of the analysis while allowing for the aggregation and smoothing of occasional deviations and anomalies. By consistently generating and evaluating the index, this tool provides a means to monitor operational status, facilitate comparisons among different stores and locations, and predict trends, risks, and optimization opportunities.

This integrated approach highlights the application of modern big data analysis methods, including regression models and discriminant analysis, thus ensuring the practical relevance of the results.

The approach under consideration is analogous to Altman model by incorporating a set of indicators that significantly influence the performance of various retail outlets within a nationally represented company.

3.2. The use case

From a methodological perspective, the proposed analytical framework identifies potential use cases as practical applications, demonstrating their capability to assess and optimize retail performance indicators. It engages with theoretical applications, examining them through applicable approaches to support the empirical validation of the model. Additionally, the framework offers a structured basis for comparing alternative strategies and evaluating their impact on key business outcomes in real retail environments.

From a methodological standpoint, various situations illustrate the necessity of implementing a structured analytical framework, which involves a multidimensional index. This section emphasizes key cases where integrating this approach offers a comprehensive analytical and comparative framework. The proposed structure consists of three main components: the analysis of the external environment, the performance evaluation of retail stores, and the evaluation of focused interventions (Fig.1).

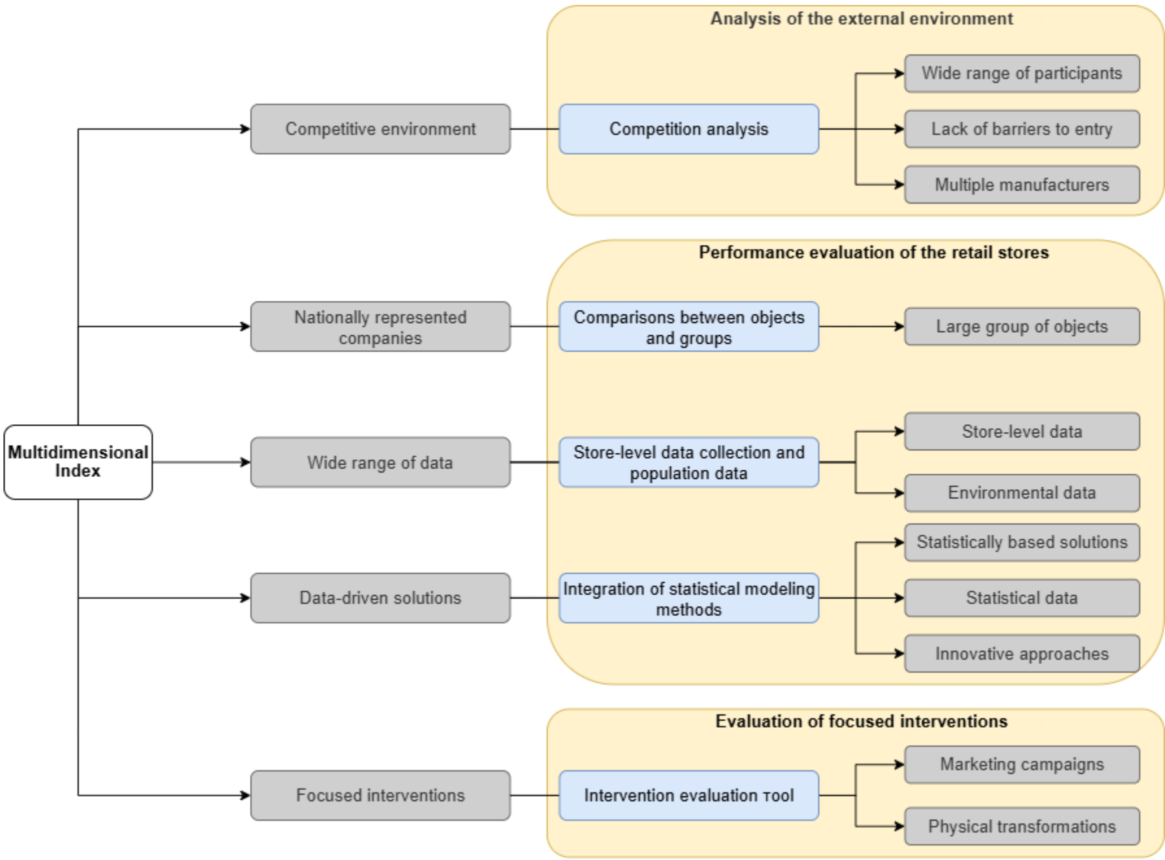

Fig. 1 Tree of use cases

3.2.1. Analysis of the external environment

The proposed index can be used in highly competitive market environments. The presence of high competition increases the need for an objective, multidimensional tool that allows for comparability, ranking, and diagnosis of business practices, both internally within a company and concerning the external environment.

3.2.1.1. Competition analysis

3.2.1.1.1. Market Participants

In markets where nationally represented retail chains and small independent operators coexist, a comprehensive analytical framework is crucial for accurately assessing performance. The proposed index not only places each retail entity within its competitive context but also allows for comparisons across different segments, considering factors such as operational scale, geographic reach, and product variety. This approach helps identify strategic positioning opportunities and uncover potential vulnerabilities in a rapidly changing environment.

3.2.1.1.2. Entry barriers

Low entry barriers in the FMCG trade give rise to a high degree of fluctuation in the sector, including frequent entries and exits of new participants. This implies the need for continuous monitoring of efficiency through a statistically stable and adaptive index, capable of capturing short-term and long-term trends. This ensures that decision-makers can react proactively to market shifts while maintaining long-term strategic coherence.

3.2.1.1.3. Manufacturers and competitive advantages

The proliferation of manufacturers in the FMCG domain creates a competitive matrix with substantial heterogeneity in pricing, quality, and brand equity. Within this context, the multivariate index serves as an evaluative instrument for measuring the capitalization of the product assortment to generate competitive differentiation. By benchmarking portfolio performance, the index enables the identification of latent growth opportunities.

3.2.2. Performance evaluation of the retail stores

3.2.2.1. Nationally represented companies

Within nationally represented chains with multiple locations, the index can serve as a primary tool for monitoring and strategically managing operational performance. It allows for standardized performance assessment and is a basis for decision-making.

3.2.2.1.1. Large number of outlets

With a relatively homogeneous network of retail outlets, the index is used in constructing internal benchmark models. The comparability of the sites in terms of location, size, product mix, and service is a suitable component for aggregate indicators and comparable key performance indicators.

3.2.2.2. A wide range of data

The effectiveness of the index is based on the presence of a rich and structured database, covering both the internal parameters of the retail and external influences. The high degree of analyticity is determined by the integration of multifactor analysis. Each of the commercial trade points is analyzed in the context of its specific environment.

3.2.2.2.1. Store-level data

A key prerequisite for the adequate functioning of the index is the collection of detailed information at the store level. This creates limitations in terms of the profile of companies that can benefit from the formation of a baseline assessment of internal efficiency. For this purpose, the company must ensure the collection of a broad base of metrics, including turnover, average basket, number of transactions, product rotation, etc.

3.2.2.2.2. Environmental Information

The inclusion of external variables increases the analytical value of the index, making it sensitive to environmental conditions and allowing for fair comparison between entities in different regions. This implies access to information related to the business environment and the potential of the customers. The data that is needed falls within the scope of national statistics and covers indicators such as population density, purchasing power, and accessibility of the store. The information provided demonstrates a strong ability to analyze and interpret data.

3.2.2.3. Transition to data-driven solutions

The proposed index constitutes a methodologically sound instrument aligned with the contemporary retail sector that emphasizes data-driven decision-making as a strategic imperative. Through the integration of advanced statistical modeling techniques and machine learning algorithms, the index enables the generation of empirically grounded retrospective evaluations while simultaneously providing predictive insights into the prospective performance of retail outlets. The methodology supports the implementation of adaptive operational strategies capable of responding to dynamic market conditions and consumer behavior patterns.

3.2.2.3.1. Statistically based decisions

The proposed methodology is oriented towards organizations that construct their strategic and operational frameworks upon empirically validated data and quantitative evidence. Within this context, the application of the developed index functions as a rigorous analytical instrument for the validation of managerial and market-oriented hypotheses, the optimization of internal and external business processes, and the systematic identification of latent patterns and behavioral regularities in consumer interactions.

3.2.2.3.2. Companies with deep sets of statistical data

The index finds application in the presence of a deep set of historical and current data. The multidimensionality of the approach considered finds application in subsequent applications aimed at forecasting using time series, cluster analysis, and regression modeling to detect latent dependencies.

3.2.2.3.3. Innovative approaches

The developed index can be used as a key input variable within dynamic and adaptive management systems for commercial operations. In this context, the index can be used to support processes in statistically sound pricing, maintaining a product assortment, as well as for implementing personalized marketing strategies based on spatiotemporal patterns of consumer behavior. In this way, the index becomes an element of a broader analytical ecosystem that allows for predictive and adaptive management decision-making.

3.2.3. Evaluation of focused interventions

3.2.3.1. Focused interventions

The proposed methodology can serve as a tool to evaluate the effectiveness of various marketing and sales strategies aimed at enhancing the performance of physical products. This encompasses marketing activities, adjustments in sales policies, and physical transformations of the entity itself. By analyzing the index value, we can identify statistically significant changes in consumer behavior and financial outcomes. Additionally, the index facilitates the analysis and comparison of products in a controlled environment, allowing for the assessment of the impact of specific interventions.

3.2.3.2. Intervention evaluation tool

The index serves as a comprehensive analytical tool for evaluating the effectiveness of strategic interventions in the sales environment. These interventions may include pricing and promotional campaigns, rebranding, reorganizing the sales area, and introducing new product lines. By quantitatively and comparatively measuring several key indicators, the index offers an objective basis for assessing the results achieved and aids in making informed management decisions moving forward.

3.2.3.2.1. Marketing campaigns

The proposed index serves as a statistically grounded tool for assessing the effectiveness of marketing campaigns in the retail sector. Incorporating multidimensional indicators such as sales uplift, transaction value, and conversion rates allows for the isolation of the specific effects of campaigns from wider market fluctuations. This methodological approach facilitates comparative analysis across various promotional strategies, including price reductions, bundling tactics, loyalty programs, etc.

3.2.3.2.2. Physical transformations

Organizations that prioritize evidence-based solutions can incorporate the index as a crucial element in their methodological frameworks for evaluating the impact of targeted interventions. This methodology is applicable in analyses that follow a series of physical interventions in retail outlets, utilizing experimental designs and control-experimental groups. The approach entails preparing a statistically robust assessment to establish the cause-and-effect relationships between the actions implemented and the resultant changes in retail outlet performance.

4. METHODOLOGY

The methodology for creating an integrated index to evaluate the performance of physical stores involves several key phases: generating an initial list of performance indicators, normalizing the values of these indicators, checking for correlation and collinearity among the indicators, applying Multiple Discriminant Analysis (MDA), calculating the integrated index, validating the results to ensure the accuracy of the method.

4.1. Initial list of performance indicators

The selection of indicators is performed by prior knowledge and an overarching conceptual framework that outlines the main processes and factors affecting the performance of a retail outlet. An initial list of thirty quantitative indicators was compiled based on their measurability, practical applicability, and analytical potential (Table 1). These indicators encompass both internal and external variables and are categorized into several functional groups: sales potential, staff efficiency, service efficiency, inventory management, customer behavior, location, financial sustainability, profitability, and physical characteristics. The indicators are categorized into three main groups: Operating, Financial and External environment. Second level is separated by several functional groups (Fig.2)

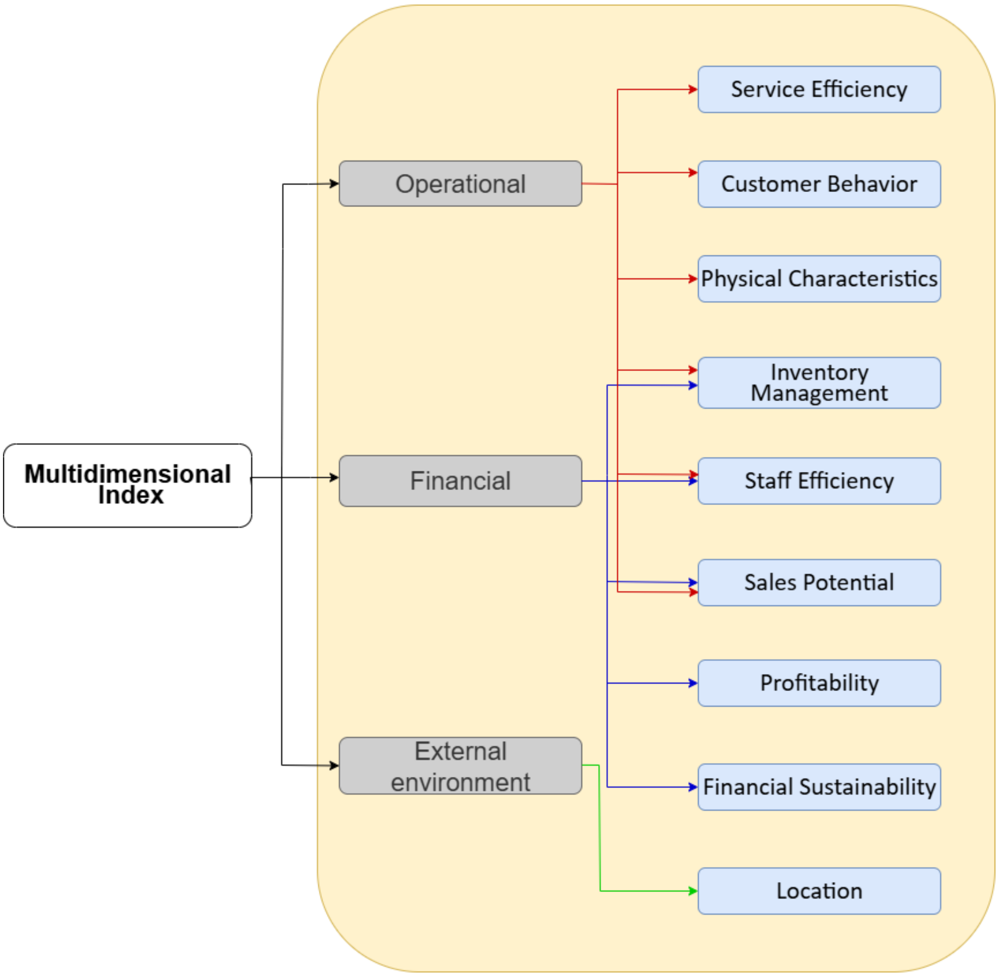

Fig.2 Hierarchical tree representing the main groups of indicators

Sales Potential. The indicators in this group assess an entity's ability to convert physical retail space into steady revenue streams. These metrics evaluate the efficiency of asset utilization and allow for benchmarking across distinct locations. This benchmarking helps identify spatial layouts and merchandising strategies that maximize yield per unit area. Analyzing these indicators offers insights into the outlet`s performance in relation to its capacity and the surrounding commercial environment.

Staff Efficiency. The indicators in this group assess the effectiveness of human resource management and utilization. The observed factors serve as primary determinants of operational output and are linked to sales performance and customer service quality.

Metrics such as sales per person and labor input-to-sales ratios provide objective measures of workforce efficiency in generating commercial output. These indicators form the basis for evaluating productivity, the efficiency of work schedules, and the connection between personnel costs and input.

Service Efficiency. The indicators in this group are used to evaluate the operational performance of retail entities. The features measure the quality of customer service and the response time, which helps identify bottlenecks and assess customer satisfaction concerning operational efficiency. This set of indicators forms a multidimensional framework that provides a systematic basis for comparing performance levels across various retail entities and organizational structures.

Inventory Management. This section includes indicators that evaluate the effectiveness of inventory management. These features assess the ability to maintain variety, freshness, and availability in response to customer demand. Systematic optimization of operational processes, focusing on inventory management, improves throughput and minimizes resource waste, enhancing overall productivity.

Customer Behavior. This group of indicators focuses on the intensity and structure of customer behavior, including visits and purchases. Understanding these features clarifies the dynamics of consumer flow by analyzing the average composition of transactions. This analysis provides insights into purchasing patterns, the efficiency of product mixes, upselling strategies, alignment with consumer demand profiles, and the ratio of store visitors to completed transactions. This ratio serves as a direct measure of conversion efficiency.

Location. Location factors provide an external context for the entity. They account for some variations in performance that are not attributed to internal processes but rather to the characteristics of the surrounding environment. The indicators considered in this group suggest an analysis related to the geographical features of the area in which the site is located, the surrounding infrastructure, and the demographic features of the region under consideration.

Financial Sustainability. This group assesses the organization's ability to maintain a strong financial structure. The indicators analyzed are not only crucial but also essential in evaluating risk, liquidity, and the organization's responsiveness to the constantly evolving market landscape.

Profitability. Profitability is a key measure of the economic efficiency of a store. Important indicators such as net profit and profit margin serve as valuable tools for assessing financial returns on operations, regardless of the retail scale. Another crucial aspect of profitability is effective cost management, which ensures that financial resources are allocated optimally to achieve the highest possible commercial return. By monitoring operational expenditures in relation to sales outcomes, businesses can identify inefficiencies and make informed budgetary adjustments.

Physical Characteristics. This group includes structural parameters such as facility structure and type, number of parking spaces, accessibility for people with disabilities, opening hours, etc. While these indicators are relatively immutable in the short term, they significantly affect capacity, accessibility, and attractiveness.

The initial list of indicators includes financial, operational, and external categories, highlighting the overlap between them based on various hierarchical levels and cross-sections. At the second hierarchical level of the presented groups, several categories contain indicators related to both financial and operational processes, which are part of the first hierarchical level, as illustrated in Figure 3.

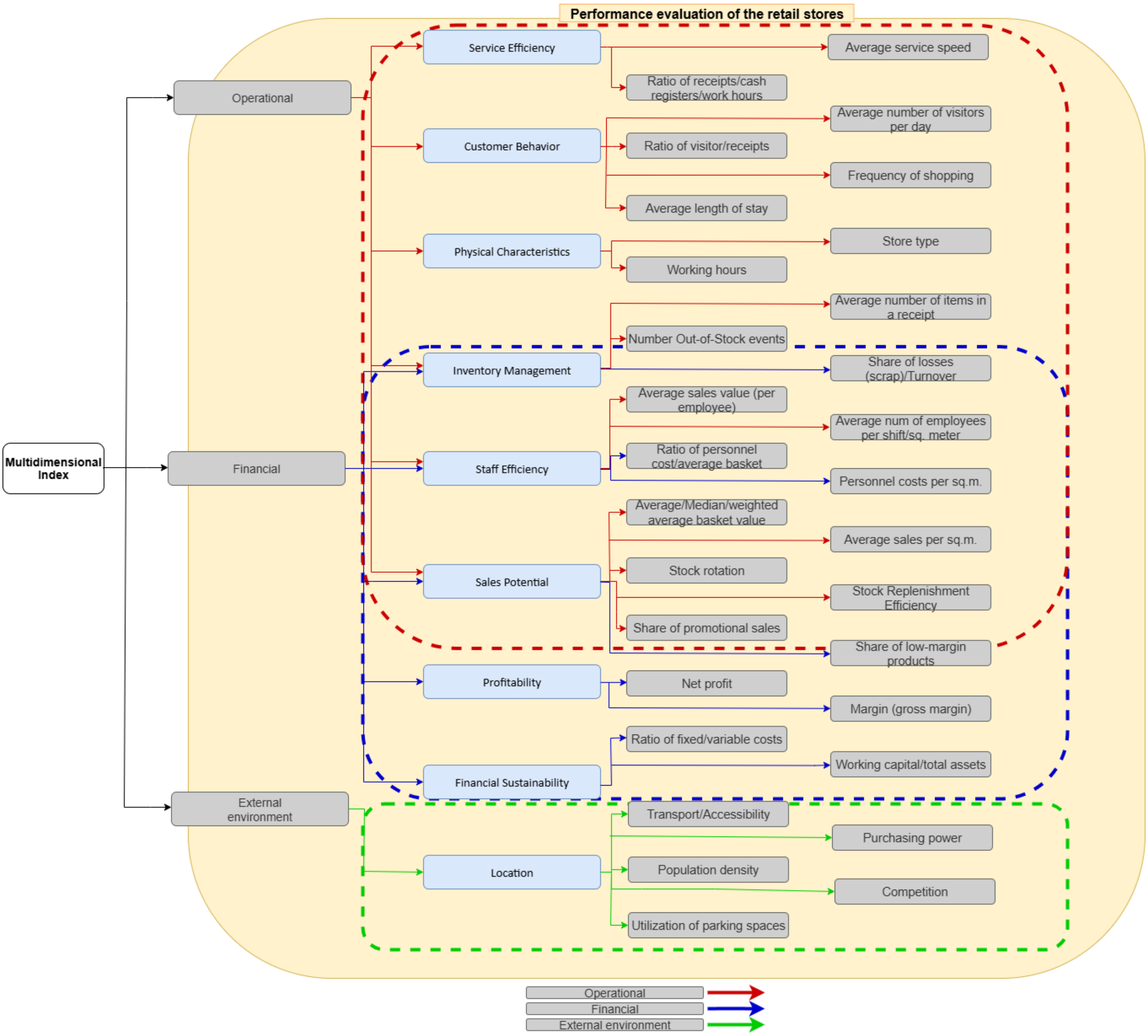

Fig.3 List of indicators distributed by hierarchical levels

4.2. Data preparation

Normalization is a crucial step in the process of creating a multidimensional index. Its purpose is to standardize the measurement scales of indicators that are expressed in different units, such as percentages, absolute values, densities, or ratios. This process facilitates aggregation and ensures that individual metrics can be compared effectively.

Given the different variability and distribution of the indicators, a mixed approach will be employed for normalization. The specific method chosen will depend on the following factors:

- The presence of extreme values (outliers)
- The shape of the distribution (normal or skewed)
- The standard deviation and range of values

4.2.1. Z-score normalization

Z-score normalization, also known as standard score or standardization, is a method for scaling data based on its mean and standard deviation [18]. This process facilitates easier comparison of features with different units or ranges.

Given a single data point x that represents an original value for indicator m:

$$z = \frac{x - \mu}{\sigma}$$

Where:
z - normalized value
x - original value
μ - mean of values
σ - standard deviation

4.2.2. Min-max normalization

Min-max normalization is a data transformation technique that rescales features to a range between 0 and 1. This method is commonly used in machine learning, data preprocessing, and statistics to normalize values, especially when the data distribution is not Gaussian, and it is important to retain outliers [18].

Let x be a single data point:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

Where:
x - original value
x' - normalized value
$\max(x), \min(x)$ - the minimum and maximum values in the dataset

4.2.3. Robust scaling

Robust scaling is a normalization technique that utilizes the median and interquartile range (IQR) instead of the mean and standard deviation, making it highly resistant to outliers. This method transforms data by subtracting the median and dividing by the IQR. As a result, it centers the data around zero and scales it based on the spread without being affected by extreme values [19].

$$x' = \frac{x - Median(x)}{IQR(x)}$$

Where:
x - original value
x' - normalized value
$Median(x)$ – median of the data

$$IQR(x) = Q_3(x) - Q_1(x)$$

Where:
Q_1, Q_3 – the quartile of observation value x

When various methods are used to normalize input indicators, it is essential to standardize the values before combining them into a composite index. To achieve this, a secondary transformation is applied through min-max normalization to all indicators that have not already been normalized using this method. This process brings all values to a consistent scale within the interval [0,1], ensuring that the indicators are comparable and preventing distortion of the result.

4.3. Correlation and multicollinearity

4.3.1. Correlation

The next step from the methodological point of view is to establish the correlations between each pair of indicators. Once these correlations are established, a correlation matrix is created. This square matrix contains the correlation coefficients for each pair of variables. The correlation coefficient measures the linear relationship between two variables, ranging from -1 (a perfect negative correlation) to 1 (a perfect positive correlation). The correlation matrix can be used to capture the dependencies between the variables.

For instance, if $X_1, X_2, \dots, X_n$ ar n e variables, the correlation matrix R can be represented as:

$$R = \begin{vmatrix} rho_{11} & rho_{12} & \cdots & rho_{1n} \\ rho_{21} & rho_{22} & \cdots & rho_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ rho_{n1} & rho_{n2} & \cdots & rho_{nn} \end{vmatrix}$$

Where ρ_{ij} is the correlation coefficient between X_i and X_j.

4.3.2. Multicollinearity

Multicollinearity refers to the linear relationships that exist between independent variables. It indicates a linear combination of two variables. Multicollinearity is typically observed in models that include a set of variables that are significantly correlated not only with the dependent variable but also with one another [20].

Multicollinearity can lead to distorted or misleading results. Addressing the issue of observed interrelationships among data helps improve the model by selecting appropriate indicators.

A useful method to assess multicollinearity is the Variance Inflation Factor (VIF). VIF measures how much the variance of the estimated regression coefficient increases when the independent variables are correlated [20, 21].

VIF is calculated with the following equation:

$$VIF_j = \frac{1}{1 - R_j^2}$$

Where:
VIF_j – Variance Inflation Factor for predictor X_j
R_j^2 - Coefficient of determination from a regression of X_j on all the other independent variables

The Variance Inflation Factor measures how much the variance of a regression coefficient is inflated due to multicollinearity with other predictor variables.

- A VIF value of 1 indicates no correlation between a given predictor and others in the model.
- VIFs between 1 and 5 suggest moderate correlation that may be acceptable depending on context.
- VIF values above 5 signal potential issues with multicollinearity
- Values greater than ten are often considered problematic for statistical inference.

4.4. Multiple discriminant analysis

The next step in the methodological framework is MDA. The method under consideration is a supervised classification technique used to classify a set of observations into predefined groups based on their individual characteristics. This method is particularly useful in classification tasks or when predicting an event, where the outcome is qualitative. For example, it can be used to determine whether a commercial retail item is profitable or not [14]. Establishing the main group distinctions is a crucial step in the process. The number of groups is determined by the purpose of the problem being solved and the available data.

The next steps in the process involve analyzing the indicators and deriving a linear combination that most effectively describes the differences between the previously established groups. A set of discriminant coefficients is determined and applied to the real data of the entity under study. This approach allows for the classification of retail into mutually exclusive groups.

The current methodology examines two categories of retail outlets: those that are profitable at the end of the month and those that operate at a loss. By differentiating between these two groups, the approach takes on a one-dimensional perspective [14].

After calculating the correlation coefficients and assessing multicollinearity among the initially selected indicators, the subsequent task is identifying the key variables to be included in the index calculation. The initially established list of variables is subject to reduction to establish an index based on a suitable number of indicators. Each variable undergoes comprehensive analysis, including a set of various methods:

- Establish the statistical significance of the variables being analyzed.
- Determine the relative contribution of each independent variable.
- Assess the interrelationships among the relevant variables and eliminate any meaningfully overlapping indicators.
- Observe the forecasting accuracy of the various profiles.
- Utilize expert assessment based on prior information.

The main objective of MDA is to identify $k-1$ discriminant functions, where $k-1$ represents the number of groups, which maximize the ratio of between-group variance to within-group variance, thereby enhancing group separation.

4.4.1. Within group variance

The Within-Group Scatter Matrix evaluates the dispersion of individual observations around their respective group means. It measures how closely the data clusters within each class and is essential for differentiating between-group and within-group variance [25].

The Within-Group Scatter Matrix can be defined as:

$$S_w = \sum_{i=1}^{G}\sum_{j=1}^{n_i}(x_{ij} - \bar{x}_i)(x_{ij} - \bar{x}_i)^T$$

Where:
G - number of groups (classes)
n_i - number of observations in group i
x_{ij} – the j observations in group i
$\bar{x}_i$ – the main vector of group i

The final S_w matrix has dimensions $p\,x\,p$ where p is the number of variables (features). In the formula for the Within-Group Scatter Matrix, the transpose operation, indicated by T, is applied to ensure that the result is a square matrix — specifically, a symmetric positive semi-definite matrix. This is crucial in multivariate analysis, as the scatter matrix generalizes variance and covariance to multiple dimensions.

4.4.2. Between-Group Scatter Matrix

The Between-Group Scatter Matrix, also called the Between-Class Scatter Matrix, quantifies the variability of group means concerning the overall (global) mean [25]. It measures how well the groups are separated in the feature space.

$$S_B = \sum_{i=1}^{G} n_i(\bar{X}_i - \bar{X})(\bar{X}_i - \bar{X})^T$$

Where:
$\bar{X}_i$ – mean vector of the group i
$\bar{X}$ – overall mean vector

This matrix assesses the deviation of each group's mean from the global mean, adjusted for the size of each group n_i. High values in S_B suggest that the group means are well-separated, which is advantageous in classification problems. S_B is a symmetric $p\ x\ p$ matrix, where p represents the number of features.

In Linear Discriminant Analysis (LDA), the main goal is to find a linear transformation that enhances class separability. This involves projecting high-dimensional data into a lower-dimensional space while retaining as much class-discriminative information as possible. The effectiveness of this transformation is measured by maximizing the ratio of between-group scatter to within-group scatter, formally expressed as:

$$a = arg \max_{a} \frac{a^T S_B a}{a^T S_w a}$$

This is a generalized eigenvalue problem, and the solution provides up to G−1 discriminant functions.

Each function:

$$Z = a^T x$$

represents a projected axis that best separates the group centroids.

After calculating the discriminant function Z, the observation is assigned to the group whose projected value is closest to that group’s centroid, using the Euclidean distance or another appropriate metric based on the underlying assumptions.

In MDA, the objective is to identify a set of linear combinations of predictors, represented as $a^T x$ (i.e., the discriminant functions), that maximize the separation among multiple groups (more than two classes). This is accomplished by maximizing the generalized Fisher criterion.

The original discriminant function in MDA is defined as a function of the following form [14, 22]:

$$Z = a_1x_1 + a_2x_2 + a_3x_3 \dots a_nx_n$$

Where:
$a_1, a_2, a_3, \dots a_n$ – discriminant coefficients
$x_1, x_2, x_3, \dots x_n$ – independent variables

The discriminant vector a defines a direction in feature space that best separates the classes. This is achieved by solving the generalized eigenvalue problem:

$$S_B a = \lambda S_w a$$

obtain the discriminant axes (eigenvectors a) that correspond to the largest eigenvalues λ, which define the discriminant functions Z.

The next step involves calculating the coefficients for the chosen indicators. The established set of variables aims to enhance the overall profile of the index and create an integrated tool for differentiating performance.

4.5. Validation

It is essential to check the results obtained using the methodological framework considered. In the process of validating the index under consideration, it is important to consider two main areas: statistical validation of the model, showing its discriminatory and predictive power, as well as business justification (Business Logic), establishing the correctness of the approach from a business point of view.

4.5.1. F tests

A suitable method for assessing the model's discriminatory qualities is the F value. The F statistics offer a quantitative measure of the ratio between explained and unexplained variance in the model. The information presented demonstrates a strong capacity for analysis and interpretation.

The F-test, developed by R. Fisher, is an important statistical tool commonly used in hypothesis testing and statistical inference. This test is based on the ratio of two independent chi-squared distributions, each adjusted for their respective degrees of freedom. Under the null hypothesis, this ratio follows an F-distribution [23].

Two sample F tests

The F-test is commonly used to compare the variances of two independent normal populations [24]. Let's examine two distinct samples:

Let σ_1^2 and σ_2^2 are the population variances of the two samples $X_{11}, X_{12}, X_{13}, \dots, X_{1n}$ and $X_{21}, X_{22}, X_{23}, \dots, X_{2n}$. With following hypothesis:

$$H_0: \sigma_1^2 = \sigma_2^2 \text{ and } H_0: \sigma_1^2 \neq \sigma_2^2$$

The equation for test statistics is as follows:

$$F = \frac{V_1^2}{V_2^2}$$

Where:

V_1^2 and V_2^2 are variances of two samples

Where:

$$V_1^2 = \frac{1}{n_1 - 1}\sum_{i=1}^{n1}(X_{1i} - \bar{X}_1)^2$$

$$V_2^2 = \frac{1}{n_2 - 1}\sum_{i=1}^{n2}(X_{2i} - \bar{X}_2)^2$$

Where:
$n_1 - 1$ - Degrees of freedom of n_1 sample
$n_2 - 1$ - Degrees of freedom of n_2 sample

4.5.2. Analysis of Variance (ANOVA)

Analysis of Variance is a statistical method used to determine whether significant differences exist between several independent groups. It does this by examining the variance both within and between these groups simultaneously. ANOVA partitions the total variability into components caused by systematic effects and random errors.

The primary statistic used in ANOVA is the F-value, which represents the ratio of variance between the groups to variance within the groups. This ratio serves as a basis for making inferences about whether the observed differences are likely due to random chance or if they reflect true underlying differences among the groups.

4.5.2.1. One-way ANOVA

The test is based on dividing the total variance into variance between groups and variance within groups, which provides a framework for hypothesis testing under the assumptions of independence and normality [24]. A significant F-value indicates that not all group means are equal, necessitating further analysis to identify specific group differences. The null hypothesis is formulated as:

$$H_0 = \mu_1 = \mu_2 = \cdots = \mu_{k'}$$

Where:

μ_1 , μ_2 – mean of the group.

The F-statistics is computed as:

$$F = \frac{MS_{Between}}{MS_{Within}}$$

The Mean Square Between Groups represents the average variation between the group means and the overall mean, calculated as the sum of squares between groups divided by their degrees of freedom:

$$MS_{Between} = \frac{SS_{Between}}{k-1}$$

Mean Square Within Groups represents the average variability within each group and can be expressed as:

$$MS_{Within} = \frac{SS_{Within}}{N-k}$$

Where:
k – is the number of groups
N – is the total sample size
Which can be represented as:

$$SS_{Between} = \sum_{i=1}^{k} n_i(\bar{X}_i - \bar{X})^2$$

Where:
n_i – number of observations
$\bar{X}_i$ - sample mean of group i
$\bar{X}$ – overall mean of all observations

A larger $SS_{Between}$ suggests greater separation between groups, which could indicate a significant effect of the independent variable.

$$SS_{Within} = \sum_{i=1}^{k}\sum_{j=1}^{n_i}\left(X_{ij} - \bar{X}_i\right)^2$$

Where:
X_{ij} - value of the j^{th} observation in group i

SS_{Within} indicates the variation that group means do not explain, highlighting the level of dispersion within each group.

4.5.2.2. Two-Way ANOVA

Two-Way ANOVA is a statistical method that examines the effects of two independent categorical variables (factors) on a single continuous dependent variable. It also evaluates interaction effects between these factors. This method builds on One-Way ANOVA by adding a second factor, enabling researchers to assess the main effects (the independent influence of each factor) and whether the impact of one factor depends on the level of the other factor.

The general model for a Two-Way ANOVA with interaction is:

$$Y_{ijk} = \mu + a_i + b_j + (ab)_{ij} + \epsilon_{ijk}$$

Where:
Y_{ijk} - observed value of the dependent variable
μ - overall mean
a_i – effect of the i-th level of factor A
b_j- effect of the i-th level of factor B
$(ab)_{ij}$ - interaction effect between level i of A and level j of B
ϵ_{ijk} - random error (assumed normally distributed with mean zero and constant variance)

The primary hypotheses in Two-Way ANOVA can be expressed as:

Main effect of Factor A:

$H_0: a_1 = a_2 = \cdots = a_n = 0$

Main effect of Factor B:

$H_0: b_1 = b_2 = \cdots = b_n = 0$

Interaction effect: $H_0: (ab)_{ij} = 0 \ \forall i, j$

Each hypothesis is evaluated using an F-test, where the F-statistics is computed as:

$$F = \frac{MS_{effect}}{MS_{error}}$$

Where:

$$MS_{effect} = \frac{SS_{effect}}{df_{effect}}; \qquad MS_{error} = \frac{SS_{error}}{df_{error}}$$

The variation explained by a specific factor in the ANOVA model can be expressed with:

$$SS_A = \sum_{i=1}^{a} n_b (\bar{Y}_i - \bar{Y}..)^2 ; \qquad SS_B = \sum_{j=1}^{b} n_a \left(\bar{Y}_j - \bar{Y}..\right)^2$$

$$SS_{AB} = \sum_{i=1}^{a} \sum_{j=1}^{b} n(\bar{Y}_{ij} - \bar{Y}_i - \bar{Y}_j + \bar{Y}_j)^2$$

Where:
$\bar{Y}_i$ – mean of i in group A
$\bar{Y}_j$ - mean of j in group B
$\bar{Y}_{ij}$ – mean of i, j
$\bar{Y}$ – grand mean

The degrees of freedom represented the number of observations minus the number of estimated parameters:

$$df_A = a - 1; \qquad df_B = b - 1$$

$$df_{AB} = (a - 1)(b - 1)$$

Where:
a – number of observations in factor A
b – number of observations in factor B

The unexplained variation — the sum of squared differences between each observation and its group mean can be expressed as:

$$SS_{error} = \sum_{i-1}^{a}\sum_{j=1}^{b}\sum_{k=1}^{n_{ij}}(Y_{ijk} - \bar{Y}_{ij})^2$$

Where:
Y_{ijk} - individual observation i, j
$\bar{Y}_{ij}$ - mean of observations i, j
n_{ij} - number of observations i, j
a, b – levels of factor A and B

$$df_{error} = N - ab$$

Where:
N – total number of observations

When there are two categorical predictors affecting a continuous outcome, it is important to assess whether the interaction between these two predictors is significant. This analysis can commonly be used in various fields such as experimental design, marketing (for example, promotions across different regions), and retail analytics.

4.5.3. Validation through business logic

Business validation is a crucial stage in developing a multidimensional index used to observe the performance of individual outlets. While statistical validation provides insights into the model's discriminatory and predictive power, business validation focuses on the method's applicability in a real-world business context, considering the unique aspects of the specific business logic.

Business logic. The first stage of business validation involves clearly defining the business logic and strategic objectives, which serve as the foundation for building the index. During this phase, hypotheses are formulated regarding the expected relationships between individual indicators and the overall business results. This initial phase is crucial, as it establishes the framework for interpretation and ensures the index's business relevance.

Logical consistency. The next step involves assessing the logical consistency of the indicators. This assessment determines the direction of their influence and their compatibility with established business practices, facilitating the development of a weighting system that highlights strategically significant factors in correspondence with the particular business field.

Simulation analyses. Applying a set of simulation analyses allows for the verification of the reliability of the results produced by the index, especially under extreme values of key indicators.

Benchmarks. An important part of the business validation process is comparing the index values with actual business results and their changes over time. During this comparison, benchmarking against similar entities or markets is useful for evaluating the universality of the approach.

Representatives of the business environment under consideration should be appropriately involved in the business validation process, thus ensuring transparency of the methodology, in order to improve traceability and transparency of the methodology.

5. CONCLUSION

The study examines traditional approaches to measuring retail performance in the context of the current economic situation, viewing them through the lens of the complex multidimensional nature of modern retail ecosystems in a fast-moving consumer goods environment. In the course of the work, a number of opportunities for improving the measurability of retail outlets were identified.

The conceptual framework proposed in the document introduces a validated multidimensional index that integrates financial operational, behavioral, spatial, and contextual factors. Through robust data normalization, statistical correlation testing, variance inflation factor analysis, and multiple discriminant analysis, the index achieves a balanced representation of key indicators while reducing multicollinearity and preserving statistical significance. The result is an evidence-based tool that supports comparative analysis, benchmarking, predictive modeling, and strategic decision-making at store, regional, and national levels. The index goes beyond mere profitability, observing by embedding dimensions such as staff productivity, customer conversion, inventory management, and location-specific factors, thereby enabling a holistic assessment of operational performance. Its flexibility allows the application to diverse use cases, including market competition analysis, evaluation of focused interventions, and the transition towards data-driven decision-making in retail chains. Furthermore, the integration of external environmental and demographic variables ensures comparability across heterogeneous markets and supports fair performance ranking. The framework aligns with modern analytical ecosystems by providing a diagnostic and predictive instrument.

The multidimensional index is considered a methodologically sound, scientifically validated, and practically applicable tool for improving operational efficiency, competitive positioning, and sustainable growth in retail chains.

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Num	Feature	Description	Measurement	Cluster level 1	Cluster level 2
1	Average basket value	This metric reflects the average amount spent by each customer. It tracks the development of specific stores, purchasing power, and market positioning, which are essential for formulating future strategies.	Amount	Operational	Sales Potential
2	Average sales per sq.m.	This measure assesses revenue related to the retail space area. It highlights the efficiency of the retail location and facilitates comparisons between stores of varied sizes.	Amount/sq.m.	Operational	Sales Potential
3	Stock rotation	This indicator observes how quickly merchandise is sold and replenished. It is vital for optimizing inventory management.	Number	Operational	Sales Potential
4	Stock Replenishment Efficiency	This metric measures the rate at which merchandise is replenished in relation to the retail space. It is key to optimizing product rotation and minimizing stale inventory.	Number/per work hour	Operational	Sales Potential
5	Share of low-margin products	This figure indicates the share of revenue generated from low-margin items. It provides insights into the primary customer profile and aids in shaping pricing strategies.	Percent	Financial	Sales Potential
6	Share of promotional sales	This metric reveals the proportion of revenue generated through discounts. It offers valuable information about customer sensitivity to promotions and assists in pricing strategies and segmenting customers.	Percent	Operational	Sales Potential
7	Average sales value (per employee)	This feature evaluates the entity's revenue concerning the number of employees, serving as an indicator of productivity and efficiency.	Amount/employee	Operational	Staff Efficiency
8	Personnel costs per sq.m.	It analyzes the ratio of labor costs to the area, offering insight into the cost efficiency of the entity being evaluated.	Amount/sq.m.	Financial	Staff Efficiency
9	Ratio of personnel cost/average basket	This indicator reflects the effectiveness of human resource management in terms of generated revenue and serves as a measure of operational efficiency.	Percent	Financial	Staff Efficiency

Num	Feature	Description	Measurement	Cluster level 1	Cluster level 2
10	Average number of employees per shift/sq. meter	It assesses the optimal distribution of staff during peak and off-peak hours to maintain a balance between costs and service quality.	Employee/sq.m	Operational	Staff Efficiency
11	Average service speed	This feature illustrates the effectiveness of customer service, which directly impacts on customer satisfaction and shopping frequency.	Clients/min (hour)	Operational	Service Efficiency
12	Ratio of receipts (cash registers)/work hours	The ratio observes the efficiency of cash registers, staff performance, and the workload across different cash register areas.	Bons/cash registers	Operational	Service Efficiency
13	Average number of items in a receipt	It measures the depth of customer shopping, highlighting the effectiveness of cross-selling and product assortment.	Number	Operational	Inventory Management
14	Number Out-of-Stock events	This feature covers the availability ratio, a critical factor in minimizing lost profits.	Percent	Operational	Inventory Management
15	Share of losses (scrap)/Turnover	Losses from shortages, theft, and spoilage. Important for inventory control. Indicator for monitoring the effectiveness of control.	Percent	Financial	Inventory Management
16	Average number of visitors per day	Traffic levels are critical when calculating sales potential, and they hold both operational and strategic significance.	Number	Operational	Customer Behavior
17	Ratio of visitor/receipts	Visitor purchase conversion rates indicate how well visitors are transforming into buyers. This metric helps assess the appeal and effectiveness of marketing campaigns.	Percent	Operational	Customer Behavior
18	Frequency of shopping	Indicator for monitoring customer loyalty. Provides information on the overall effectiveness, the strength of the brand	Number	Operational	Customer Behavior
19	Average length of stay	The duration customers spend in the store is a key indicator. It reflects the store's appeal and effectiveness, impacting impulsive buying behavior.	Min (hour)	Operational	Customer Behavior
20	Transport/Accessibility	This indicator evaluates factors such as transportation and infrastructure. It is essential for forecasting traffic patterns.	Scale	External environment	Location

Num	Feature	Description	Measurement	Cluster level 1	Cluster level 2
21	Purchasing power	This assesses the economic potential of the area being considered. It serves as an external factor impacting sales and is useful in planning locations.	Scale	External environment	Location
22	Population density	This feature provides a basis for predicting the maximum potential volume of customer traffic in a specific area	People/sq.m.	External environment	Location
23	Market Competition Analysis	This measures the level of competition in the market, influencing market share and pricing strategies.	Number	External environment	Location
24	Utilization of Parking spaces	This reflects how convenient it is for customers to access the service or product; it can either limit or encourage attendance.	Number	External environment	Location
25	Ratio of fixed/variable costs	The ratio under consideration highlights the adaptability of the cost structure, which is crucial when developing a budget framework	Percent	Financial	Financial Sustainability
26	Net profit	A key indicator of a retail outlet's financial sustainability and efficiency in resource management	Amount	Financial	Profitability
27	Margin (gross margin)	Measures the profitability of sales and is the basis for controlling the pricing and assortment strategy.	Percent	Financial	Profitability
28	Working capital/total assets	It reflects the outlet's liquidity and flexibility in addressing operational needs and adapting to unexpected market changes.	Amount	Financial	Financial Sustainability
29	Store type	This measurement highlights the specific characteristics of the store (internal division scale), which influence various productivity levels and cost structures.	Scale	Operational	Physical Characteristics
30	Working hours	This indicator impacts the outlet's ability to generate revenue and serve different customer segments effectively.	Hours	Operational	Physical Characteristics

Table 1: Table of the initial set of indicators