Електронний журнал «Ефективна економіка» включено до переліку наукових фахових видань України з питань економіки (Категорія «Б», Наказ Міністерства освіти і науки України № 975 від 11.07.2019). Спеціальності – 051, 071, 072, 073, 075, 076, 292.
Ефективна економіка. 2023. № 8.

DOI: http://doi.org/10.32702/2307-2105.2023.8.7
УДК 330.4:004.8

O. Liashenko,
Doctor of Economic Sciences, Professor, Professor of the Department of Economic Cybernetics, Taras Shevchenko National University of Kyiv
ORCID ID: https://orcid.org/0000-0002-0197-4179
B. Yakymchuk,
Postgraduate student, Taras Shevchenko National University of Kyiv
ORCID ID: https://orcid.org/0000-0003-2574-3815

MODELING AN INVESTMENT DECISIONS SUPPORT SYSTEM IN GROCERY RETAIL

О. І. Ляшенко,
д. е. н, професор, професор кафедри економічної кібернетики, Київський національний університет імені Тараса Шевченка
Б. Б. Якимчук,
аспірант, Київський національний університет імені Тараса Шевченка

МОДЕЛЮВАННЯ СИСТЕМИ ПІДТРИМКИ ПРИЙНЯТТЯ ІНВЕСТИЦІЙНИХ РІШЕНЬ У ПРОДУКТОВОМУ РИТЕЙЛІ

The significance of effective financial decision-making cannot be overstated for any company's future growth. However, this process often faces challenges arising from inadequate information and the subjective inclinations of decision-makers, resulting in instability. The emergence of financial decision support systems, driven by advancements in computer technology, has brought about some improvements in decision quality. Nevertheless, these systems still grapple with issues such as human-centered leadership, insufficient intelligence, and suboptimal efficiency, leaving room for improvement to fully cater to decision-makers' needs.

In recent years, the grocery retail sector in Ukraine has encountered *significant challenges. The advent of the pandemic has induced substantial shifts in consumer behavior, prompting the exploration of novel avenues for service provision and service enhancement. Additionally, the backdrop of ongoing war has introduced further complexities, characterized by air raids and power outages. Within this context, the domain of grocery retail necessitates meticulous allocation and planning of investment budgets aimed at fostering organic growth and sustaining elevated profitability levels. Within the sphere of grocery retail, the principal catalyst for organic expansion remains the augmentation of the network, specifically the identification of prospective locations for new retail outlets. In light of this, the study presents a discerning approach to bolster decision-making processes pertinent to the establishment of new stores. This approach is grounded in the application of machine learning methodologies. The research proposes the development of a support system for investment decision-making, structured with components for data collection and aggregation, transformation through machine learning algorithms, and visualization mechanisms for ongoing monitoring and decision support encompassing the entirety of the investment portfolio. The paper delineates a novel amalgamation of financial modeling techniques and advanced machine learning methods aimed at augmenting the efficacy of investment choices. This holistic approach seeks to mitigate the intricacies arising from contemporary challenges and uncertainties, thereby contributing to the viability and sustainability of investments in the dynamically evolving landscape of grocery retail.*

Рівень значущості ефективного прийняття фінансових рішень неможливо переоцінити для майбутнього розвитку компанії будь-якої індустрії. Однак цей процес часто стикається з проблемами, що виникають через недостатню інформацію та суб'єктивні погляди осіб, хто приймає рішення, що призводить до його нестабільності. Поява систем підтримки прийняття фінансових рішень, спричинена прогресом у комп'ютерних технологіях, призвела до деяких покращень у якості прийняття рішень. Тим не менш, ці системи все ще стикаються з такими проблемами, як людино-центричне лідерство, недостатній рівень розвитку та субоптимальна ефективність інтелектуальної системи, що залишає простір для вдосконалення для повного задоволення потреби осіб, що приймають рішення.

В останні роки сектор продуктового ритейлу в Україні зіткнувся зі значними проблемами. Поява пандемії спричинила суттєві зміни в поведінці споживачів, що спонукало до пошуку нових шляхів надання та покращення послуг. Крім того, на тлі триваючої війни створюються додаткові *складності, які характеризуються повітряними тривогами та перебоями з електроенергією. У цьому контексті сфера роздрібної торгівлі продуктами потребує ретельного розподілу та планування інвестиційних бюджетів, спрямованих на сприяння органічному зростанню та підтримку високих рівнів прибутковості. У сфері продуктового ритейлу головним каталізатором органічної експансії залишається нарощування мережі, а саме визначення перспективних локацій для відкриття нових магазинів. В контексті описаних тенденцій дослідження представляє підхід до посилення процесів прийняття рішень, пов'язаних із відкриттям нових магазинів. Цей підхід побудований на основі застосування методів машинного навчання. Дослідження пропонує розробку системи підтримки для прийняття інвестиційних рішень, що сформована з компонентів для збору та агрегації даних, перетворення за допомогою алгоритмів машинного навчання та механізмів візуалізації для постійного моніторингу та підтримки прийняття рішень, що охоплює весь інвестиційний портфель. У статті описано нове поєднання методів фінансового моделювання та методів машинного навчання, спрямоване на підвищення ефективності інвестиційних рішень. Цей підхід спрямований на зниження ризиків, що виникають через сучасні виклики та невизначеності, сприяючи таким чином життєздатності та сталості інвестицій на ринку продуктового ритейлу, що динамічно розвивається.*

Keywords: *investment decision support systems, machine learning, grocery retail, decision-making.*

Ключові слова: *системи підтримки прийняття інвестиційних рішень, машинне навчання, продуктовий ритейл, прийняття рішень.*

Statement of the problem in general and its connection with important scientific or practical tasks. The landscape of grocery retail has undergone profound transformations due to the confluence of the COVID-19 pandemic and the subsequent full-scale Russian invasion of Ukraine. These events have engendered substantial shifts in consumer behavior, consequently giving rise to emergent market trends. This fluidity in market dynamics has introduced a heightened level of unpredictability, thereby augmenting the intricacy inherent in operational and strategic planning endeavors.

The core facet of investment endeavors within grocery supermarket chains resides in organic expansion, primarily realized through the establishment of new retail outlets. This strategic undertaking facilitates audience enlargement by either extending geographical coverage to novel regions or intensifying service accessibility to broader population segments. Conventionally, the decision-making process for store initiation revolves around external location attributes, encompassing variables such as population density, residential property dynamics, and the competitive landscape proximal to the store's geographic coordinates.

However, the evolving landscape, notably propelled by the rapid growth and deepening influence of e-commerce, has engendered a transformation in the profitability and efficacy of conventional brick-and-mortar establishments. This shift can be attributed to pronounced shifts in consumer behavior. Notably, the ascent of e-commerce has significantly reshaped shopping paradigms. Furthermore, the backdrop of the COVID-19 pandemic has catalyzed transformative shifts in consumer preferences within the Ukrainian market, with traditionally conservative consumer segments acclimating to the convenience of e-commerce channels. This, in turn, has accelerated the digital transformation of the retail sector, fostering a surge in the adoption of delivery services. As indicated by a comprehensive study conducted by Deloitte, a discernible trend has emerged wherein the online sales growth rate has notably outpaced that of conventional offline channels [2].

Within the framework of the aforementioned market trends, the conventional brick-and-mortar supermarket chain is compelled to approach its development and expansion strategy with heightened efficacy. Leveraging available free cash flow for investments in physical expansion demands a meticulous focus on maximizing efficiency. This imperative arises from the realization that each unit of physical space yields diminishing returns in contrast to the growth potential of online channels.

Hence, the focal point of this study resides in the construction of a comprehensive decision support system. This system is dedicated to facilitating accurate project assessment, optimizing location selection, and augmenting profitability within the pursuit of an optimal spatial expansion strategy. Through the integration of advanced analytical methodologies, the proposed system aims to enable precise projections, strategic site choices, and enhanced financial outcomes, thus navigating the intricate interplay between the physical and digital dimensions of retail operations.

Analysis of recent research and publications, which initiated the solution of this problem and on which the author relies, the selection of previously unsolved parts of the general problem, which is the subject of his article. The exploration of Decision Support Systems (DSSs) was initiated in the 1970s when Scott et al. introduced the concept of management decision systems and their application in computer-assisted decision-making processes [4].

The evolution of DSS has unfolded across four stages (Fig. 1):

- Management Information Systems (MIS);
- Transaction Processing Systems (TPS);
- Decision Support Systems (DSS);
- Intelligent Decision Support System (IDSS).

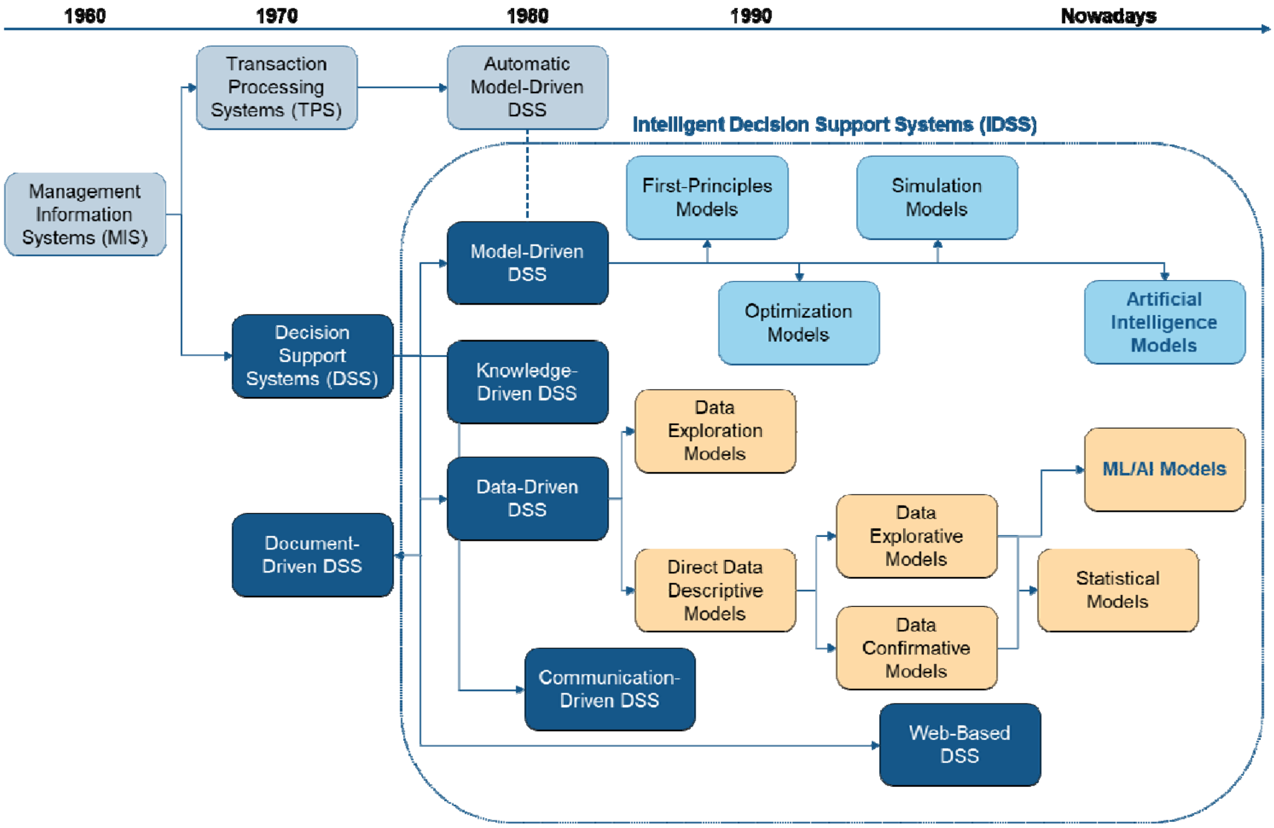

Fig. 1. Evolution of the development of decision support systems

Source: formed by the authors using [3, 7].

The culmination of advanced decision support systems' evolution is witnessed in the form of Intelligent Decision Support Systems (IDSS), a paradigm that emerged during the late 1980s and 1990s. Contemporary iterations of these systems are progressively incorporating machine learning techniques, intelligent analysis of extensive datasets, and artificial intelligence capabilities. Predominantly, these systems adopt a data-driven approach, classified as Data-Driven DSS, while others adhere to a model-driven paradigm, referred to as Model-Driven DSS. The maturation of IDSS underscores the significance of data accumulation and its potential to derive profound insights from vast repositories of both structured and unstructured information.

Foreign financial DSSs emerged in the 1980s, and notable systems were developed and deployed by EXCUCON Systems, Capex, and American Airlines. Ongoing scholarly efforts have proposed diverse design schemes, enhancing functionalities and broadening application domains [6].

Recent studies have centered their attention on advancing the field of financial decision support systems. The study authored by Zhou, Ong, and Liu [9] focuses on the design and implementation of an Enterprise Financial Decision Support System. This system is built upon the foundation of Business Intelligence (BI) methodologies. Through an in-depth exploration of the system's design and implementation, the paper sheds light on how BI principles can be harnessed to empower more informed and strategic financial decision-making within enterprises. The study by Jia et al. [6] presents the design of a digital and intelligent financial decision support system leveraging artificial intelligence.

The research conducted by Kozlov, Tomashevska, and Kuznetsov [10] focuses on the application of optimization models within financial decision support systems (DSS). The study explores the architecture of the DSS, emphasizing the interplay among key components such as user interface, database, analytical tools, and communication infrastructure. The functional model of the DSS is elucidated with a proposed block diagram encompassing three primary subsystems. The system's open architecture enables adaptability for expansion and integration with external databases.

In recent research, several studies have also discussed the utilization of decision support systems for initiating new store openings within the domain of grocery retail. The research paper, authored by Harahap et al. [5], delves into the strategic domain of optimal retail location identification. Employing the robust framework of a Decision Support System (DSS) in conjunction with the Simple

Additive Weighting (SAW) method, the study presents an intricate yet practical approach to tackle the complex task of pinpointing optimal retail locations. By harnessing the power of these methodologies, the paper endeavors to offer valuable insights and guidelines for businesses navigating the nuanced landscape of retail expansion and growth.

Formulation of the goals of the article (task statement). This article aims to construct a robust support system tailored to facilitating investment decisions within grocery retail. Its primary objective is to optimize the decision-making process concerning the establishment of new locations while concurrently exploring avenues for enhancing the overall profitability of these projects.

Presentation of the main material of the study with a full justification of the obtained scientific results. The development of an Investment Decision Support System tailored for the grocery retail industry can significantly enhance strategic decision-making when it comes to opening new stores. This system harnesses advanced data analytics, predictive modeling, and business intelligence to empower retailers with informed insights into potential locations, market trends, and profitability projections. By leveraging this technology, grocery retailers can optimize their expansion strategies, minimize risks, and maximize returns on investment. There can be derived various benefits from the implementation of the Investment Decision Support System for grocery retail organic expansion:

1. Data-Driven Insights: The Investment Decision Support System utilizes a vast array of data sources, including demographic information, consumer behavior patterns, economic indicators, and competitive landscapes, to provide retailers with a comprehensive understanding of potential markets. This data-driven approach enables more accurate decision-making by identifying areas with high growth potential and consumer demand.

2. Location Optimization: One of the critical factors in the success of a new grocery store is its location. The Investment Decision Support System employs sophisticated algorithms and geospatial analysis to identify optimal store locations based on factors such as population density, income levels, proximity to competitors, and transportation networks. This ensures that each new store is strategically positioned for maximum foot traffic and customer accessibility.

3. Risk Mitigation: Opening new stores involves inherent risks, including competition, changing consumer behaviors, and economic fluctuations. The IDSS assesses these risks and provides retailers with risk mitigation strategies, allowing them to make more informed decisions and allocate resources effectively.

4. Profitability Projections: Through financial modeling and scenario analysis, the IDSS can estimate the potential profitability of new store openings. Retailers can simulate different scenarios, adjusting variables such as store size, pricing strategies, and operational costs to understand the potential impact on their bottom line before making investment decisions.

5. Resource Allocation: The IDSS assists retailers in allocating resources optimally by identifying areas with the highest potential return on investment. This prevents oversaturation in specific markets and guides the allocation of capital and human resources to areas with the most significant growth opportunities.

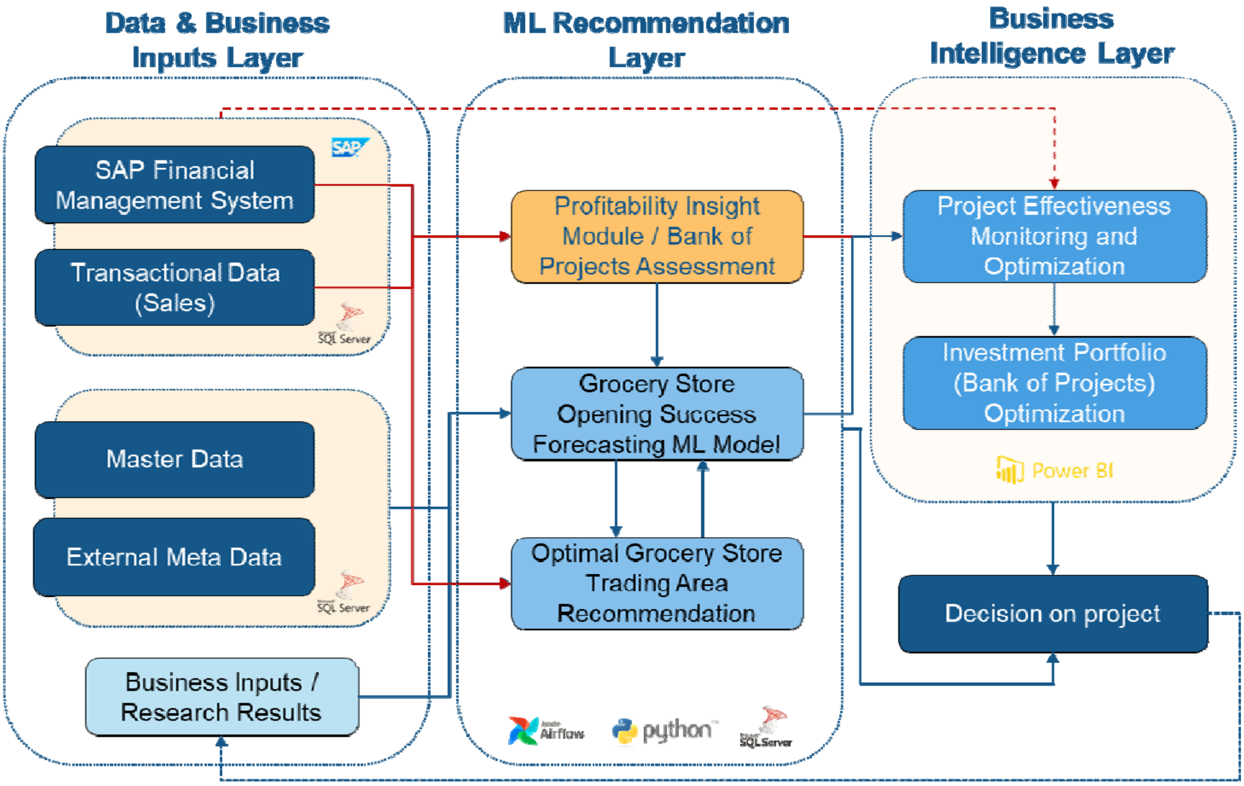

Fig. 2. Architecture of Investment Decision Support System

Source: formed by the authors.

The proposed architecture for the Decision Support System (DSS) is designed to facilitate the selection of optimal new store projects and to monitor their outcomes (Fig. 2) closely. This architecture encompasses three interconnected layers, each playing a crucial role in ensuring the efficiency and success of the decision-making process:

1. At the foundational level of this resource model, the Data and Business Inputs Layer assumes the role of a comprehensive repository. This layer intricately gathers essential data inputs and business regulations. It serves as a data hub, seamlessly collecting information from a multitude of sources, including SAP Financial Management System and internal transactional systems. This holistic data aggregation empowers the subsequent layers with a robust and diverse set of insights, forming the bedrock for informed decision-making.

2. The ML Recommendation Layer harnesses the power of advanced machine learning algorithms to construct a holistic assessment of the probability of success for each project. These algorithms, imbued with the ability to discern patterns and relationships within the data, provide invaluable insights into the potential outcomes of new store ventures. Beyond this, the layer goes a step further by offering recommendations on the optimal parameters for the new stores to enhance profitability. This innovative approach ensures that decisions are informed by data-driven projections and future-focused considerations.

3. Crowning the architecture is the Business Intelligence Layer, a pivotal element that transforms data into actionable insights. This layer serves as a nexus for consolidating and presenting complex data in an intelligible and visually engaging format. Through intuitive dashboards and dynamic visualizations, managerial personnel gain unfettered access to a wealth of information. Key performance indicators, including sales, gross margin, EBITDA dynamics, and pivotal project profitability metrics such as Internal Rate of Return (IRR) and Net Present Value (NPV), are elegantly displayed. This empowers decision-makers to monitor and track the progress of launched projects with unparalleled precision.

The Data and Business Inputs Layer: The decision support system utilizes several data sets within its data warehouse to generate accurate financial data for project assessment. These data sources include:

- SAP Financial Management System: Data related to cash and liquidity management, including bank account balances, cash flow projections, cash positions, and bank reconciliation statements. This source is also used to generate financial statements, including balance sheets, income statements, and cash flow statements. These reports provide insights into an organization’s financial performance and position.

- Transactional Data refers to a detailed record of individual sales transactions that occur between a business and its customers. Each transaction includes information about the products purchased, quantities, prices, dates, loyal customer details, payment methods, and any relevant discounts or promotions. This data is crucial for understanding customer behavior, evaluating product performance, optimizing pricing strategies, and making informed business decisions.
- Master Data: This data includes store-specific characteristics such as total and trading store area, the number of cash registers and self-service cash registers, and the number of operation hours of the store.
- The External Data source is a data hub generated from open-source instruments. It provides comprehensive information about the urban environment, encompassing key aspects such as city attributes, population metrics, geographical expanse, and the sociodemographic landscape. It furnishes data regarding the proximity of the site to the city’s central hub, assesses the accessibility of parking facilities, and employs a binary factor to discern whether the location is situated within a bustling shopping center. Furthermore, this dataset scrutinizes the competitive landscape by quantifying the number of rivals operating within the same radius as the chosen location, shedding light on the proposed site’s market saturation and potential viability.

In the initial pilot phase of the system, a subset of 78 chain stores was chosen to serve as the training dataset for the recommender system. These selected stores were emblematic of two distinct supermarket chains, each falling under the categories of convenience stores, discount stores, and premium supermarkets. The establishment timeline for all these facilities spanned from 2018 to 2022, deliberately excluding any antiquated format stores and those that did not undergo substantial developmental phases prior to the onset of the evaluation period. This meticulous selection criterion ensured that the dataset encapsulated modern and relevant store formats, positioning the system to make informed recommendations aligned with contemporary retail dynamics.

The cornerstone of the ML Recommendation Layer is the Profitability Insight Module, often referred to as the "Bank of Projects." This module serves as a sophisticated engine that not only assesses the potential profitability of various projects but also functions as a reservoir of strategic initiatives awaiting evaluation and selection. Its capabilities extend beyond simple profitability analysis, making it an invaluable tool in guiding strategic decision-making within the organization. The data in this preparation module is gathered in the following way:

1. The process begins with the SAP Financial System gathering comprehensive financial statement data. This data includes revenue, expenses, depreciation, interest, taxes, and other relevant financial components.

2. EBITDA is calculated by summing up Earnings Before Interest and Taxes (EBIT) and adding back Depreciation and Amortization expenses. This metric provides insight into a company's operational performance and cash generation ability.

3. Cash flow is computed based on EBITDA by incorporating changes in working capital, capital expenditures, interest, taxes, and other cash-related adjustments. The resulting value represents the actual cash generated by the business operations.

4. NPV is calculated by summing the present values of past and future cash flows and subtracting the initial investment. A positive NPV indicates that the investment is expected to generate value, while a negative NPV suggests that the investment may not be financially viable.

$$NPV = \sum_{i=1}^{n} \frac{CF_i}{CoE} \tag{1}$$

where CF_i - free cash flows generated by project / new store launch in the period i, CoE - cost of equity.

The assessment of store openings is conducted under the assumption of exclusively utilizing equity capital, thereby excluding the possibility of debt financing. In this context, the discount rate applied is based on the cost associated with procuring equity funds. To quantify the cost of equity, the evaluation employs the Capital Asset Pricing Model (CAPM) [1], which is computed using the following formula:

$$CoE = R_f + \beta\left(R_m - R_f\right) + CRP \quad (2)$$

where R_f – the risk-free rate of return, R_m – expected market return, β – the coefficient of the asset sensitivity to market dynamics, and CRP – a premium for sovereign risk.

5. IRR is determined by finding the discount rate at which the net present value of future cash flows becomes zero. This rate signifies the rate of return that the investment is expected to generate.

$$NPV = \sum_{i=1}^{n} \frac{CF_i}{IRR} = 0 \quad (3)$$

Conducting a comprehensive evaluation of each individual branch facilitates a systematic and consistent monitoring process, conducted on a recurring monthly basis, aligned with the conclusion of the reporting cycle. This approach enables a dynamic assessment of the most recent financial metrics' ongoing impact on each branch's actual or projected profitability. By diligently tracking this evolving financial landscape, organizations can promptly identify trends, discrepancies, and potential areas for optimization.

Furthermore, the collected dataset from these evaluations serves as a valuable resource with multifaceted applications. Apart from its role in ongoing monitoring, this dataset holds immense potential for training and refining machine learning models. By leveraging historical performance data and correlating it with various contextual factors, these models can be developed to discern intricate patterns, forecast future outcomes, and generate predictive insights. This symbiotic relationship between rigorous evaluation and machine learning innovation empowers organizations to make informed decisions, anticipate market shifts, and enhance each branch's overall efficiency and profitability.

The initial recommendation system facilitates the estimation of the likelihood of project success by transforming the IRR metric into an ordinal variable:

$$y_t = \begin{cases} 0, \ if & IRR \le CoE \\ 1, \ if & CoE < IRR \le CoE + \sigma_r \\ 2, \ if & CoE + \sigma_r < IRR \end{cases} \quad (4)$$

Utilizing the established three-phase variable indicative of store opening success, a classification machine learning model can be constructed to make informed predictions. The dataset comprises a diverse array of features [8]:

- Binary/Ordinal Features: ownership structure (whether the object is owned or leased), location format (whether the store is situated in a residential estate, mall, or business center), assortment cluster (categorization based on product assortment).
- Nominal Features: retail format (classification into convenience, discount store, supermarket, or premium supermarket), region (geographical location of the store).
- Continuous Features: capital expenditure (investments in construction and equipment), total and trading floor area, distances to various landmarks (city center, nearest shopping center, business center, bus stations, subway, and regional highways), median real estate value per square meter within a 1 km radius.

This meticulously curated dataset was subjected to rigorous testing across multiple machine learning models, including logistic regression, probit-regression, neural network modeling, discriminant analysis, decision tree construction using the C5.0 algorithm, Random Forest, and gradient boosting. Among these, XGboost emerged as the optimal model with an accuracy of 80.1% on the test dataset [8].

Grocery retailers can effectively harness this XGboost model for strategic decision-making. By automatically evaluating available locations within urban settings, the model can pinpoint priority locations, thereby enhancing the efficiency of the business development department. Given the model's high classification accuracy, it becomes a potent tool to augment the profitability of the investment portfolio, optimize cash flow, and alleviate the investment burden associated with less promising ventures.

Another module in Machine Learning Recommendation Layer – Optimal

Grocery Store Trading Area Recommendation helps to envisage diverse revenue and operational efficiency scenarios for different store's trading floor areas. This innovative capability gives retailers insights that guide them toward the most optimal decisions.

While staying attuned to contemporary retail market trends, the paramount objective is to optimize revenue generation per square meter of the trading floor. Nonetheless, a careful balance must be struck, considering that a certain threshold of traffic per square meter can influence customer experience negatively. Striking this equilibrium is vital, as excessive crowding during peak hours could deter consumers, leading to potential stock shortages and checkout queues.

In light of these considerations, the module adopts the following approach:

1. Development of a Sales Forecasting Machine Learning Model: The foundation entails constructing a robust machine learning model to predict sales specifically during the store's peak hours. This model harnesses external factors and the store's trading area to generate accurate predictions.

2. Identification of Optimal Income per Square Meter: Determining the ideal income-to-area ratio is paramount. This analysis seeks to establish a balance where increased revenue does not compromise guest satisfaction.

3. Simulation of Maximized Ratio with Customer Satisfaction Constraint: The research then proceeds to simulate scenarios aimed at maximizing the income-to-area ratio while upholding a stringent constraint on customer satisfaction. This pivotal constraint ensures that elevated revenue generation aligns harmoniously with a high level of customer contentment.

When assessing the revenue forecast model, the evaluation process led to the selection of the CatBoost model, which exhibited a Mean Absolute Percentage Error (MAPE) metric of 16.4%. This metric quantifies the model's predictive accuracy, indicating that the chosen CatBoost model provides estimations with a relatively low deviation from the actual revenue figures, demonstrating its efficacy in forecasting revenue outcomes.

The opening year of the store emerged as the pivotal factor, embodying the company's strategic evolution. This yearly approach reflects diversification, increased departments, and proprietary products. It distinguishes similar stores within a locale and lures consumers seeking novel assortments. The model relies heavily on DWT-derived clusters, which are useful for peak hours but prone to misclassifying new regions or formats, leading to prediction errors. Key location metrics include city size, proximity, 1 km radius population density (OSM-based), and competing entities.

Through this algorithmic framework, a range of enhancements can be realized within the traditional brick-and-mortar grocery retail model:

- Maximized Sales Efficiency: The algorithm aims to amplify the sales-to-square-meter ratio by suggesting the optimal trade area, bolstering revenue generation within the available retail space.
- Cost Optimization: This approach facilitates reductions in utility expenses, rental obligations, and labor costs. Consequently, these reductions contribute to lower economic purchase quantities and hasten the achievement of the break-even point.
- Streamlined Technological Footprint: The algorithm's impact is reflected in the decreased need for advanced technological equipment, leading to optimized Capital Expenditures Budgets.
- Enhanced Cash Flow Dynamics: The optimization of the cash flow structure further translates into growth in both the Internal Rate of Return and Net Present Value across the company's project portfolio.

The final two modules in ML Recommendation Layer, in their interaction with users, facilitate the delivery of valuable recommendations:

1. Viability of Store Opening: Assess the feasibility of establishing a store at the recommended location with the specified attributes.
2. Impact on Success Probability: Provide insights on whether altering the success probability is achievable through format, cluster or investment budget management modifications.
3. Optimal Launch Area: Offer guidance on identifying the most suitable area for launch, striking a balance between guest loyalty retention and maximizing revenue per square meter of floor space.

The Business Intelligence Layer within the model empowers users to engage in a comprehensive monitoring process, enabling them to gauge the efficacy of their decisions, track the ongoing progress of project evaluations, identify unanticipated factors that deviate from model predictions, and accentuate financial vulnerabilities requiring targeted improvements.

This monitoring endeavor is manifested through monthly revaluations, entailing data replication subsequent to the conclusion of the reporting cycle. This dynamic mechanism affords a succinct view of revenue dynamics over a condensed period, providing a benchmark for assessing success. Given its paramount significance, revenue is the pivotal yardstick for measuring the prowess of a retail enterprise.

A concrete instance of this layer is illustrated in Figure 3, underscoring the tangible application of these monitoring functionalities and their role in optimizing decision-making and steering financial viability.

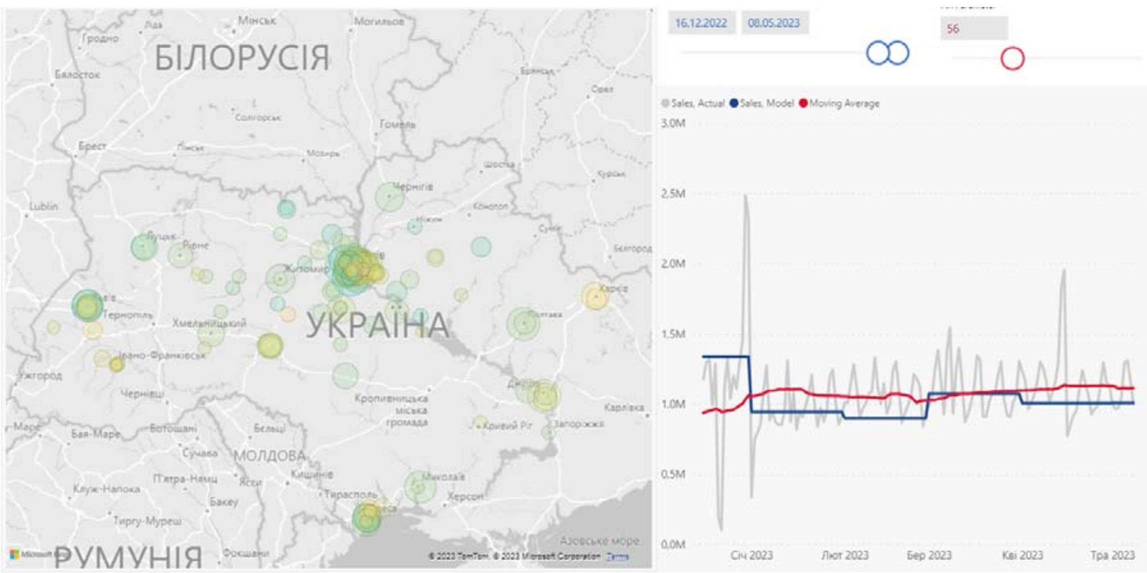

Fig. 3. Visualization of revenue monitoring and the execution of the model's strategic blueprint.

Source: formed by the authors.

Conclusions from this study and prospects for further exploration in this direction. The primary focus of investment endeavors in grocery supermarket chains lies in organic expansion through the establishment of new retail outlets. This strategic pursuit aims to broaden audience reach and cater to evolving consumer needs. However, conventional decision-making processes centered around external location attributes are being challenged by the surge of e-commerce and changing consumer behaviors. The emergence of online channels and the pandemic's impact have driven the retail landscape's transformation, prompting retailers to adopt data-driven approaches to maximize profitability and operational efficiency.

To address these challenges, this study proposes the development of a comprehensive Investment Decision Support System tailored for grocery retail. This system integrates advanced analytics, predictive modeling, and business intelligence to empower retailers with data-driven insights for selecting optimal store locations, enhancing profitability, and mitigating risks. The IDSS is structured into three interconnected layers, each contributing to the decision-making process:

- Data and Business Inputs Layer: This foundational layer serves as a data hub, collecting inputs from various sources, including SAP Financial Management System, transactional systems, and external data. It provides essential information for accurate project assessment and informed decision-making.
- ML Recommendation Layer: This layer harnesses machine learning algorithms to assess project success probability and recommend optimal store parameters. By utilizing advanced analytics, it offers insights that guide strategic decisions, optimizing location selection, and enhancing profitability.
- Business Intelligence Layer: The final layer transforms complex data into actionable insights through user-friendly dashboards and visualizations. It enables managers to monitor and track key performance indicators, facilitating ongoing project evaluation and enhancing financial decision-making.

The Investment Decision Support System utilizes historical performance data, machine learning, and financial modeling to provide a holistic approach to investment decision-making. It offers several benefits, including data-driven insights, location optimization, risk mitigation, profitability projections, and resource allocation.

The model does come with certain limitations that need to be acknowledged. One notable drawback is the relatively small sample size, which could potentially impact the accuracy of recommendations, especially when dealing with store openings in new regions or under new formats. However, it’s important to highlight that the system’s retraining capability offers the potential for dynamic accuracy improvement as the sample size grows over time.

Another potential challenge is the model’s stability. While ensembles help enhance robustness, the limited number of observations can lead to inaccuracies due to incorrect data weighting during training. This issue could be mitigated by obtaining a more extensive and diverse dataset.

Furthermore, the current sample is based on pre-war period data, which introduces a risk of error, particularly in regions experiencing population migration. To address this, incorporating up-to-date sources on population movement would be crucial when launching the decision support system.

Looking ahead, there are promising avenues for model development. Integrating additional models to guide store renovation decisions and the implementation of new technologies on a larger scale could greatly expand the project bank. This holistic approach has the potential to optimize the investment portfolio across all business projects, enhancing the overall effectiveness of the model.

In summary, while the model has its limitations, its adaptive nature, the potential for expansion, and integration with broader decision-making processes position it as a valuable tool for strategic planning and investment optimization in the evolving grocery retail landscape.

Література

1. Damodaran A. (2020), *Equity Risk Premiums: Determinants, Estimation and Implications*, 11th ed, NYU Stern School of Business. https://dx.doi.org/10.2139/ssrn.3550293

2. Deloitte (2022), "Споживацькі настрої українців у довоєнний період", URL: https://www2.deloitte.com/content/dam/Deloitte/ua/Documents/Press-release/Consumer-sentiment-of-the-Ukrainians-over-the-pre-war-period_UA.pdf (дата звернення: 14.08.2023).

3. Dhar, V., & Stein, R. (1997), *Intelligent decision support methods. The science of knowledge work,* Prentice-Hall.

4. Er M. C. (1998), "Decision Support Systems: a summary, problems, and future trends," *Decision Support Systems*, vol. 4, no. 3, pp. 355–363. https://doi.org/10.1016/0167-9236(88)90022-X.

5. Harahap, M. A. K., Hardisal, H., Ahyuna, A., and Rahim, R. (2022), "Leveraging the Decision Support System and Simple Additive Weighting Method for Optimal Retail Location Identification", *JINAV: Journal of Information and Visualization*, 3(2), 174-180. https://doi.org/10.35877/454RI.jinav1485

6. Jia T., Wang C., Tian Z., Wang B., and Tian F. (2022), "Design of Digital and Intelligent Financial Decision Support System Based on Artificial Intelligence", *Computational Intelligence and Neuroscience*, 1-7. https://doi.org/10.1155/2022/1962937

7. Sànchez-Marrè, M. (2022), *Intelligent Decision Support Systems*, Springer, Cham. https://doi.org/10.1007/978-3-030-87790-3_3

8. Yakymchuk B. and Liashenko O. (2022), "Forecasting of New Grocery Store Opening Success Using Machine Learning Algorithms", *12th International Conference on Advanced Computer Information Technologies (ACIT)*, Ruzomberok, Slovakia, pp. 203-206, doi: 10.1109/ACIT54803.2022.9913157.

9. Zhou J., Ong T. and Liu Y. (2023), "Design and Implementation of Enterprise Financial Decision Support System Based on Business Intelligence", *International Journal of Professional Business Review*. 8. e0873. 10.26668/businessreview/2023.v8i4.873.

10. Козлов В. В., Томашевська Т. В., Кузнєцов М. І. (2020), "Використання оптимізаційних моделей у фінансових системах підтримки прийняття рішень", *Статистика України*., № 1. С. 75–83. Doi: 10.31767/su. 1(88)2020.01.09.

References

1. Damodaran, A. (2020), *Equity Risk Premiums: Determinants, Estimation and Implications*, 11th ed, NYU Stern School of Business, NY, USA. https://dx.doi.org/10.2139/ssrn.3550293

2. Deloitte (2022), "Consumer attitudes of Ukrainians in the pre-war period", available at: https://www2.deloitte.com/content/dam/Deloitte/ua/Documents/Press-release/Consumer-sentiment-of-the-Ukrainians-over-the-pre-war-period_UA.pdf (Accessed 14 July 2023).

3. Dhar, V., & Stein, R. (1997), *Intelligent decision support methods. The science of knowledge work,* Prentice-Hall, Hoboken, USA.

4. Er M. C. (1998), "Decision Support Systems: a summary, problems, and future trends," *Decision Support Systems*, vol. 4, no. 3, pp. 355–363. https://doi.org/10.1016/0167-9236(88)90022-X.

5. Harahap, M. A. K., Hardisal, H., Ahyuna, A., and Rahim, R. (2022), "Leveraging the Decision Support System and Simple Additive Weighting Method for Optimal Retail Location Identification", *JINAV: Journal of Information and*

Visualization, vol. 3(2), pp. 174-180. https://doi.org/10.35877/454RI.jinav1485

6. Jia T., Wang C., Tian Z., Wang B., and Tian F. (2022), "Design of Digital and Intelligent Financial Decision Support System Based on Artificial Intelligence", *Computational Intelligence and Neuroscience*, pp. 1-7. https://doi.org/10.1155/2022/1962937

7. Sànchez-Marrè, M. (2022), *Intelligent Decision Support Systems*, Springer, Cham. https://doi.org/10.1007/978-3-030-87790-3_3

8. Yakymchuk B. and Liashenko O. (2022), "Forecasting of New Grocery Store Opening Success Using Machine Learning Algorithms", *12th International Conference on Advanced Computer Information Technologies (ACIT)*, Ruzomberok, Slovakia, pp. 203-206, doi: 10.1109/ACIT54803.2022.9913157.

9. Zhou, J., Ong, T. and Liu, Y. (2023), "Design and Implementation of Enterprise Financial Decision Support System Based on Business Intelligence", *International Journal of Professional Business Review*, vol. 8. e0873. 10.26668/businessreview/2023.v8i4.873.

10. Kozlov, V. V., Tomashevska, T. V., & Kuznetsov, M. I. (2020), "Using of Optimization Models in Financial Decision Support Systems", *Statystyka Ukrainy – Statistics of Ukraine*, vol. 1, pp. 75–83. Doi: 10.31767/su. 1(88)2020.01.09

Стаття надійшла до редакції 15.08.2023 р.