“A data science-based marketing decision support system for brand management”

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A DATA SCIENCE-BASED MARKETING DECISION SUPPORT SYSTEM FOR BRAND MANAGEMENT

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Abstract

To improve the marketing activity and brand management and justify the most effective marketing decisions, organizations should implement different information technologies, mathematical methods and models into the marketing decision support system (MDSS). The goal of this paper is to form an architecture of an MDSS, the model base of which is developed on Data Science tools, in particular regression analysis and machine learning methods. The proposed MDSS is a multi-agent information system comprising nine intellectual agents (market environment monitoring, data processing, marketing mix modeling, price policy support, portfolio management, strategic analysis, forecasting, customer segmentation, and customer classification). The functionality of these agents is realized through Data Science, which allows for the optimization of marketing activities (e.g., an effective brand management strategy and its elements (portfolio strategy, price policy, and media strategy) or solving the problems of attracting new and retaining current customers with the maximal return on marketing investments). The MDSS analyzes the marketing environment, media activity, and business indicators by constructing different models and forecasting various combinations of marketing factors to select the best one. The joint work of MDSS agents provides decision-makers with interactive reports. The research findings offer a scientific basis for making effective marketing decisions based on data, and the proposed MDSS can become part of an intelligent system for planning marketing activities.

Keywords multi-agent system, decision-making, intelligent agent, modeling, marketing strategy, marketing mix, enterprise

JEL Classification M30, C10, C61, D81

INTRODUCTION

Marketing activity, as the most critical function in the field of entrepreneurial activity, ensures stable, competitive functioning and development of the entire marketing system, considering the internal and external environment. It is based on conducting marketing research and developing a marketing strategy, which should be used to increase the productivity of the enterprise and the efficiency of meeting the needs of the end consumer (Grygoruk, 2011). Marketing research significantly affects the enterprise's profitability and its further development. Therefore, modern information technologies and practical data analysis methods have become important. In addition, there is a growing need for marketing departments to develop and implement marketing decision support systems (MDSS), which will improve the quality and speed of decision-making.

With a high rate of change, the importance of effective brand management and marketing strategy increases significantly. This is creating and managing the enterprise's brand, the main components of

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marketing research, market analysis, marketing strategy, and advertising activity. In addition, brand management requires the enterprise to solve essential issues such as finding and gaining advantages in a highly competitive market, forming a portfolio strategy, choosing effective communication channels, product distribution channels, and price policy, as well as ways to fully use its potential and correctly allocate its resources to create favorable conditions for profit.

The ability to develop agile and efficient business processes is a decisive success factor for enterprises in increasingly dynamic and complex marketing environments (Schuh et al., 2020). In the current stage of business development, it is vital to use more advanced technologies such as Data Science and machine learning to work beneficially with data, facilitate decision-making and extraction of actionable insights and knowledge (Saura, 2021). It is vital to collect and analyze all possible business features and implement them into a comprehensive data-based solution to increase business results (Hurtado et al., 2019) and improve the efficiency of brand marketing management.

Data Science-based MDSS is a way to effectively use data in the enterprise and switch to data-driven marketing. Leveraging Data Science can enable businesses to exploit data for competitive advantage by generating valuable insights. However, many industries cannot effectively incorporate Data Science into business processes (Zhang et al., 2021; Fedirko et al., 2021) and marketing management, as no comprehensive approach allows organization-wide strategic planning based on Data Science (Kayabay et al., 2022). Despite this, it is expedient to actively involve Data Science tools for the development of marketing decision support models, as well as the development of relevant MDSSs.

Developing MDSSs using small data sets usually leads to uncertain results, likely cause to incorrect decisions and significant losses. However, collecting sufficient datasets for constructing an MDSS requires high costs (Li et al., 2009). As a result, building such an MDSS is recommended for developed enterprises with high financial capabilities and which face different marketing tasks and problems in highly competitive markets daily.

This paper proposes the multi-agent architecture of an information and analytical support system for making marketing decisions based on Data Science tools (for data analysis and modeling, in particular), which can be implemented in advanced enterprises to optimize marketing strategies and improve the processes of brand's marketing management. Thus, the purpose of this study is to develop such an architecture.

1. THEORETICAL BASIS

The implementation of an information system to support marketing decision-making in the activity of the enterprise assumes that such a process is systemic, and the developed and implemented MDSS for brand management should reflect current information about the market development and the competitive environment, as well as about the effectiveness of previously adopted decisions. In addition, the system should work in automatic mode, minimizing human involvement in solving marketing tasks.

An MDSS can be highly important as it supports enterprises in collecting and processing information and decision-making by providing predictions and different models (Little, 2004). Previous research has shown that marketing specialists offered the opportunity to implement an MDSS have higher performance but need more confidence about their decisions. Performance increase due to a reliance effect (Demoulin, 2007). Van Bruggen et al. (1996) investigated the impact of the MDSS quality on decision-making. The quality was determined by the predictive precision of its simulation models. The results showed that marketing decision-making using a high-quality MDSS outperforms decision-making in marketing using a medium-quality MDSS. In a conceptual framework of MDSS proposed by Wierenga and Oude Ophuis (1997), five groups of factors are determined that potentially influence MDSS adoption, use, and success: external environment, organization, task environment, user, and implementation.

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Alexouda (2005) presented an MDSS for developing a set of substitute products based on three optimization criteria and different scenarios using the "What if analysis." Wöber (2003) investigated insights for successfully implementing an MDSS in tourism.

Aiming to support the adoption of strategic and tactical marketing decisions for brand management, the MDSS should perform the following functions:

1. Determine the compelling media mix of an advertising campaign (allocation of investments between communication channels), taking into account the accumulated information about the activity of competitors, supported by its impact on sales and other business indicators, as well as market trends, in particular regarding the media consumption of the target audience.

2. Determine each channel's optimal and necessary media pressure under certain market conditions and the enterprise's goals.

3. Determine the optimal price index level following the prices of competitors and the price elasticity of sales.

4. To be able to analyze the current market situation, the level of the competitive environment, and the strategies of individual competitors, which can affect the market structure, as well as determine the strategic vectors of competitors in order to take into account potential risks and opportunities for the enterprise in the future.

5. To be able to implement the tasks of customer segmentation and solving classification tasks regarding the optimization of advertising mailings according to the customer base (minimizing mailings to customers who will not respond to them) and minimizing the outflow of consumers from the customer base, if there is such a need.

6. To prioritize brands in the enterprise's portfolio regarding their future marketing support and development, using internal information on sales, product margins, external information on market structure, and demand dynamics to identify patterns and effectively distribute the marketing budget between different brands.

Considering the formed requirements, the proposed MDSS for brand management will be multi-agent. A multi-agent information system (MAIS) is a set of objects in the form of agents (cognitive, reactive, hybrid), which are independent, but capable of interacting to solve tasks (Bulling, 2014) jointly. These agents should be understood as computer systems that "operate autonomously in a complex dynamic environment to implement the goals for which they are designed" (Chornous, 2016).

The multi-agent architecture for developing MDSSs has been widely used in recent years. Figueroa-Pérez et al. (2021) proposed this approach to create MDSS for a new product design. Dostatni et al. (2015) presented the application of a multi-agent system to support ecodesign decision-making and proposed the agent-system structure supporting the designer. Based on the multi-intelligent-agent technology to develop the distributed MDSS, Ai et al. (2004) developed a three-layer system structure consisting of the decision customer layer, decision core layer, and decision resource layer and described the information flow between the intelligent agents of the system.

Some studies have implemented a combination of a multi-agent approach in building various DSSs and Data Science as an environment for developing models. For instance, Chornous and Iarmolenko (2017) offered a theoretical model of a DSS, based on the concept of a multi-agent information system, for predicting stock prices using data from social media. Machine-learning algorithms in this system can connect content sentiments in social networks and stock market changes. A combination of DSS and agent technologies with Data Science proves a potent tool for decision support in e-commerce. Vahidov and Fazlollahi (2003) proposed an architecture for a multi-agent DSS for e-commerce and described a prototype system for making online investment decisions.

An essential step in integrating Data Science in the planning of marketing strategy and activities is the development of an MDSS by integrating pre-

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viously accumulated knowledge based on mathematical modeling of marketing activities using Data Science technologies.

The development of the MDSS model base using various Data Science methods (in particular, regression modeling and machine learning) is envisaged to achieve this integration. For this purpose, general scientific methods (logical generalization, comparison, induction, analysis, and synthesis) also were used to identify trends in business development and Data Science implementation, analyze differences in marketing tasks, and define the main beneficial Data Science methods and models in marketing for solving them.

Mathematical modeling in marketing is being integrated into decision-based frameworks to assess customer behaviors and estimate demand. For instance, modeling the marketing mix is a powerful analytical tool for obtaining hidden knowledge and information that can directly lead to maximizing the return on marketing investments (their profitability) (Heliste, 2019). Furthermore, mathematical modeling and data analysis solve many tasks of marketing and communication activity:

- forming a marketing complex;
- optimizing a portfolio of brands and products;
- clarifying the media mix of communications;
- building a media plan for an advertising campaign;
- assessing the influence and dangers of competitors; and
- forecasting key business indicators.

Birn and Stone (2021) explore the evolution of marketing information systems and the need for businesses to use marketing information to understand and control the needs and behavior of potential customers. The authors show how marketing research helps enterprises make decisions and describe classic methods of marketing research and forecasting marketing results, as well as methods necessary for effective development, problem-solving, and quality management. Customer analysis and marketing information systems are important tools for managing the enterprise and supporting marketing strategy and decisions.

Stone et al. (2021) studied the influence of modern interactive marketing on information about customers and marketing research, in particular, how radically the methods of collecting and using such information for developing and implementing marketing strategies and elements of the marketing complex have changed. They noted the platforms that allow businesses to manage their information and interactions with customers in radically different ways through business intelligence development. Johnson et al. (2021) examined the experience of marketing departments that are entirely data-driven in their decision-making. The survey data confirm that Big Data Analytics consists of four main activities: knowledge acquisition, data quality improvement, testing, and dissemination of data analysis results. The study shows that the shift to analytics improves the quality of resources available to the marketing department and provides a model for improving marketing information quality and data-driven decision-making.

However, many issues related to the formation of the information and analytical base of marketing, the development and implementation of the strategy, and its evaluation using data analysis and new technologies require further development (Osaysa, 2022). This indicates the need to develop effective MDSSs based on modern technologies, primarily related to Data Science.

2. RESULTS

The development and launch of such an MDSS for brand management (the general functional structure of which is shown in Table 1) can provide access to operational information about business indicators. It will also enable finding hidden knowledge thanks to the display and support of developed models of the marketing mix and other Data Science technologies. In this structure, the modeling module is the support and base for others. The accumulation of internal enterprise data, data on the competitive environment, their integration, and the creation of additional knowledge by models form the transition of marketing to ef-

Table 1. General functional structure of the multi-agent MDSS "Brand's marketing management system"

Source: Developed by the authors.

Business review	Media review	Strategic decisions
• Dynamics of the market and brands • Market structure analysis • Analysis of sales depending on advertising activity • Regional analysis	• TV • Digital • Out-of-home (OOH) • Radio and Press	• Marketing and media strategy • Portfolio analysis • Media boost by brand • Client's classification and clustering • Scenario forecasting
Modeling		
• Mathematical modeling and Data Science methods implementation • Price elasticity	• ROI by media channels and brands • Seasonal ROI • Forecasting	

fective data-based decision-making through the developed system of their support.

Figure 1 contains a schematic representation of the architecture of the proposed multi-agent MDSS with a basic set of brand management capabilities. As a result, nine intelligent agents and three databases containing information on media activity, customers, and sales data are needed to support all marketing decision-making processes.

The external environment of the enterprise is a complex and dynamically changing system of relationships between the enterprise, competitors, potential consumers, and other factors that directly or indirectly affect the enterprise's activities or the market demand for goods or services (Ibrahim & Harrison, 2020). A comprehensive and detailed description of all factors influencing the enterprise is impossible due to their vast number. However, the key ones are the market activity of competitors (in particular, their advertising and sales activity), relations with potential consumers, and socioeconomic changes such as wars or economic and political crises.

The monitoring agent automatically collects data from open and closed sources of information, having previously activated paid access to them. The critical data are the media activity of all brands in key communication channels (television, Internet, radio, outdoor advertising, and the press) and data on sales in physical and monetary terms of all brands of a particular market category. Such information will create an opportunity for other agents and the system in general to analyze

Source: Developed by the authors.

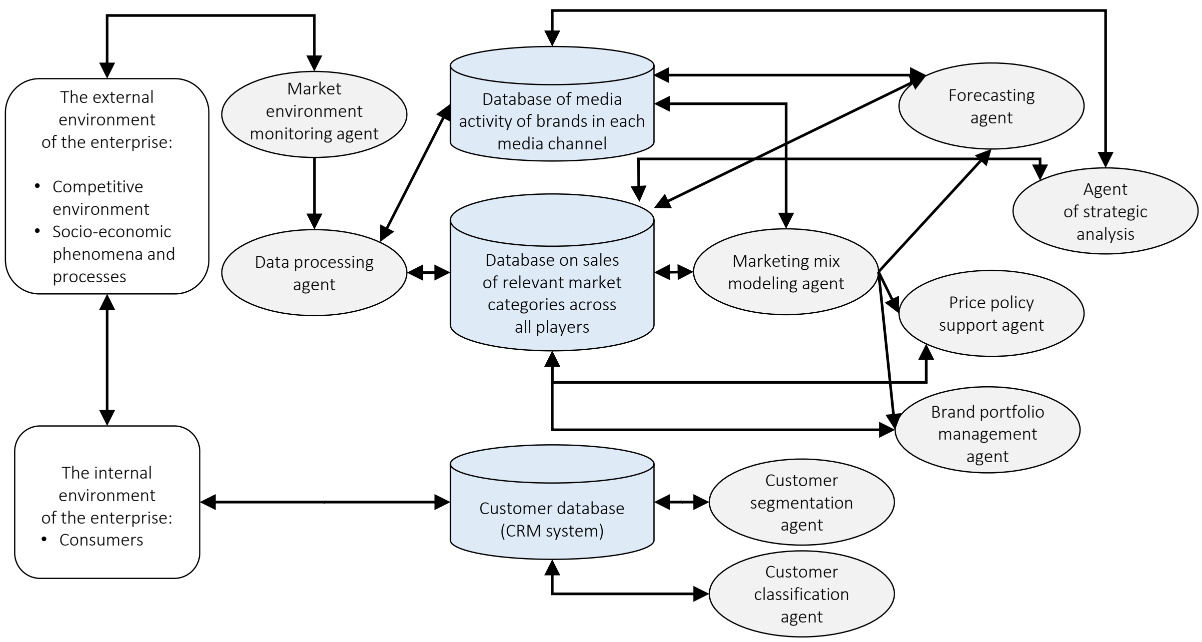

Figure 1. Architecture of the proposed multi-agent MDSS for brand management

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and form conclusions about market development trends, the marketing mix's effectiveness, and competitors' activities.

Some information collected by the monitoring agent is unstructured (except for pre-prepared reports and databases sold on the market by enterprises engaged in marketing research, such as Nielsen, Proxima research, GFK, and Kantar). Thus, it must be deciphered using artificial intelligence software, which provides the possibility of processing human language (Natural Language Processing – NLP) and, notably, analyzing the tonality of texts (Zhecheva & Nenkov, 2022), which is relevant when researching reviews about a brand or enterprise on the Internet.

The sales database contains structured information on sales dynamics in physical and value terms and prices for all brands in a particular market category. Such data are a direct reflection of market trends and market structure. Therefore, they are a vital indicator of the development of the enterprise's brands on the market (sales dynamics or market share). Furthermore, such information is essential, as it helps to create marketing mix models, assessing consumers and market reactions to the implemented marketing measures. Therefore, as a result, it determines an effective strategy based on the activities of competitors and understands the return on marketing investments (ROMI) of each element of the marketing mix.

The database with data on the media activity of brands in each communication channel is a repository for structured data on the dynamics of brand's advertising on TV (in target ratings – TRPs), on the Internet (in impressions), in outdoor advertising, in the press, and on the radio (in impressions/insertions). Such information assesses the level of the brand's competitive environment and will be used when modeling critical indicators of business development.

The internal environment of the enterprise is the entities that directly influence the enterprise's activities and interact with it. It is worth noting that the relationship between the external and internal environments occurs through marketing activities. Thus, a part of potential consumers becomes real thanks to the implementation of strategic and tactical actions by the enterprise's marketing team regarding market expansion, advertising activity, and sales system development (Habib & Ahmad, 2019).

The customer database (from the CRM system) contains current and historical data about customers in a structured form, including detailed purchase history (products, frequency, or total spending), history of interaction between the enterprise and its customer, and personal information. Filling the database is regulated by customers' consent to collecting and processing personal data, ethical beliefs, legislation, and technical capabilities of the enterprise.

Customer focus is a diverse and multifaceted concept and is a crucial element of enterprise's marketing function (Islamgaleyev et al., 2020). Thus, it is relevant to implement agents for customer segmentation and classification using Data Science methods, in particular machine learning algorithms.

The customer segmentation agent implements the methods of Data Mining and distinguishes groups of consumers based on a formed or automatically selected list of personal characteristics and features. The basic assumption and purpose of segmentation are that a separate product offer and appropriate marketing communication should be developed for different consumer segments (Huseynov & Özkan Yıldırım, 2019). Therefore, customer segmentation should be updated regularly, especially during sharp changes in consumer behavior.

The customer classification agent classifies methods based on the consumer database in order to identify the main characteristics of customers who, depending on the purpose of the classification, have, for example, a higher risk of refusing the enterprise's services (the risk of churn) or a different probability of a positive reaction to advertising mailings. This agent can identify the most valuable customer groups (Günesen et al., 2021) and the further development of appropriate marketing measures (Mo & Yang, 2022). Like customer segmentation, classification methods should also be applied regularly to maintain relevance to the market situation.

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The marketing mix modeling agent constructs models for the available target indicators of business activity (sales, market share, or traffic). It also determines the effective media mix of the advertising campaign (allocation of investments between communication channels), the optimal media pressure in each media channel under certain market conditions, and following the enterprise's goals, assessing the impact of each of them on business growth. The agent uses economic and mathematical models and machine learning methods to establish an effective marketing complex and update the models and marketing strategy with each new data and knowledge received. Data Science makes it possible to increase ROMI and improve the business results of the enterprise.

The price policy support agent receives information from the marketing mix modeling agent about the price elasticity of sales and determines the optimal price index level, considering the current dynamics of competitors' prices and their expected dynamics in the future.

In the price analysis process, a particular price increase can lead to a drop in package sales. On the other hand, it can generate an additional level of profit in the case that the price increase compensates for the reduction in sales in physical volume and vice versa – a significant increase in the price of a product can lead to a significant drop in sales in natural volumes, and the enterprise's income will decrease significantly. Accordingly, there is potential for optimization depending on the price elasticity of sales and market share in money and packages (Farm, 2020). Depending on the business goals (increasing market share in terms of money (increasing profits) or increasing market share in packages (increasing brand's penetration among consumers), recommendations for pricing policy will be fundamentally and radically different.

Based on the constructed econometric models of the marketing mix for the brand, it is possible to derive the dependence curves of the market share in money (in value terms) and the market share in packages depending on the price index level. Furthermore, the coefficients of the models at the price index indicate how the market share will change when the index increases prices for 1 unit (the nature of the relationship is linear in the case of constructing a linear regression or non-linear in the other case).

The market share in money and the market share in packages are connected through the price index: the value market share is the market share in packages multiplied by the price index, i.e.,

$$Value\ MS = Volume\ MS \cdot Price\ index. \quad (1)$$

Since the rate of change of the market share in packages (linear or non-linear) does not coincide with the rate of change of the price index (linear, but with a different growth rate), there is a non-linear dependence between the price index and the market share in monetary terms. This leads to the presence of optimization zones depending on business goals.

Figure 2 shows an example of the analysis of price elasticity and the formation of recommendations regarding the optimal price index. Depending on the business goals, this Data Science methodology turns into a flexible tool for specialists in the price policy planning department, as it is possible to formulate a recommendation on the price index level to achieve goals both in terms of market share in value and market share in packages (Chornous & Fareniuk, 2022).

The forecasting agent receives information from the marketing mix modeling agent about the impact of each factor on a critical business indicator and implements scenario forecasting, calculating for each scenario the overall level of sales, market share, traffic, or other indicators, as well as the planned ROMI. Based on the received forecasts, marketing planning specialists will decide on the most effective strategy under the set goals.

The brand portfolio management agent receives information from the marketing mix modeling agent about the ROMI of each brand and determines market capacity and demand potential based on the category sales database. By processing such information, the agent determines the priority of brands in the enterprise's portfolio and is the basis for distributing the general marketing budget between the most priority brands. The

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Source: Developed by the authors based on Chornous and Fareniuk (2022).

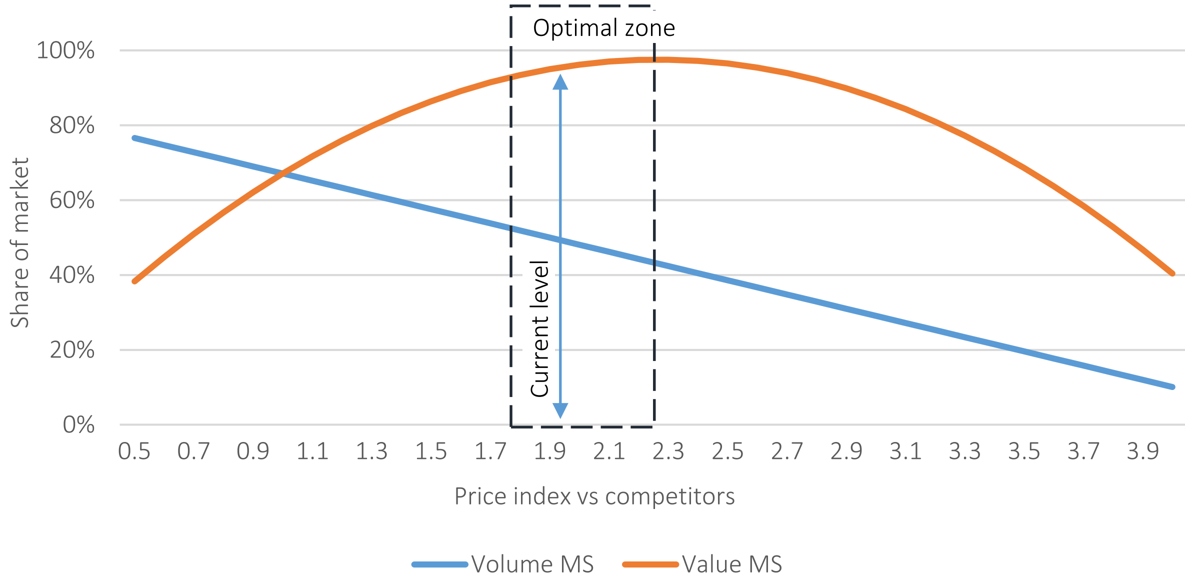

Figure 2. Example of the optimal level of the price index considering the growth of market share in money

general process of portfolio strategy optimization involves step-by-step analysis and modeling using Data Science tools, as shown in Figure 3.

Marketing mix modeling is a tool for evaluating ROMI by calculating the level of sales generated by media activity in each communication channel (equations (2)-(4)) and comparing it to the level of media investment respectively. The second step of the described process involves the calculation of the Media Boost indicator according to equation (5), which indicates the share of sales generated by media activity, i.e., it shows the contribution of media to sales in percentage. After converting such an indicator into sales volume in monetary terms and comparing it with realized media investments using equations (2)-(4), it is possible to prioritize the brands in the portfolio according

Source: Developed by the authors.

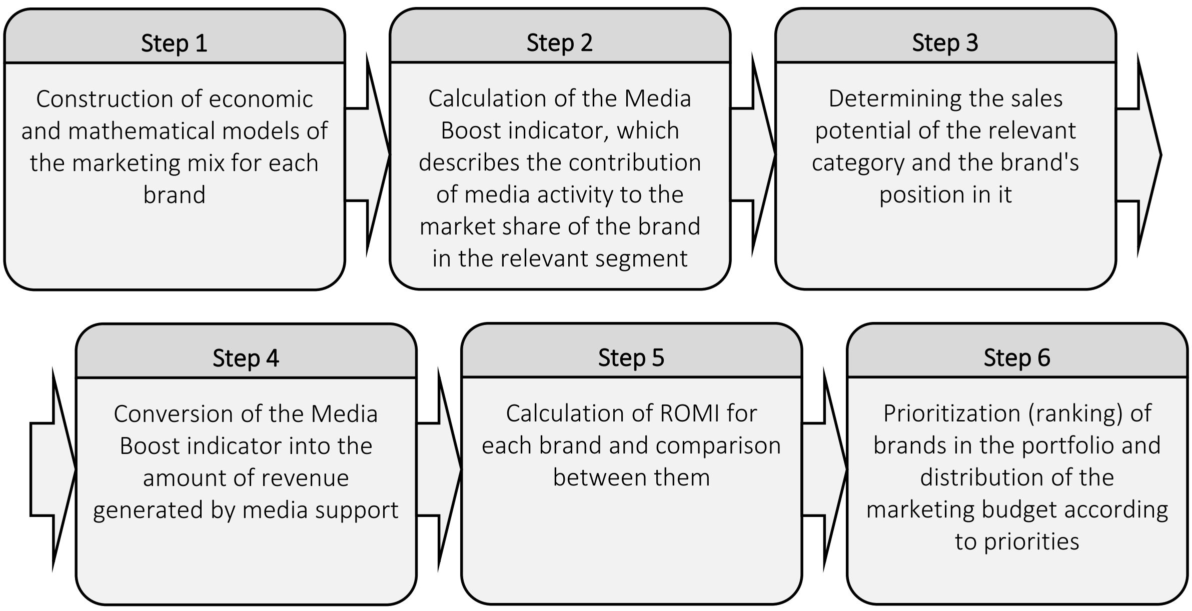

Figure 3. Approach to the formation of an effective portfolio marketing strategy

$$ROMI\ general = \frac{Media\ sales\ in\ hryvnias}{General\ media\ investments}. \quad (2)$$

$$ROMI\ TV = \frac{Sales\ from\ TV\ in\ hryvnias}{Media\ investments\ in\ TV}. \quad (3)$$

$$ROMI\ Digital = \frac{Sales\ from\ Digital\ in\ hryvnias}{Media\ investments\ in\ Digital}. \quad (4)$$

$$Media\ Boost = \frac{Sales\ from\ packaged\ media}{Total\ brand's\ sales}. \quad (5)$$

to their overall media performance as defined by ROMI. In addition, understanding each communication channel's effectiveness allows for formulating an effective media strategy for each brand, considering the competitive environment. Data Science methods may increase general profit from all brands in the enterprise's portfolio.

The strategic analysis agent uses data from the media activity and sales databases to determine the competitive level of media pressure (to achieve the brand's visibility against the background of competitors in each media channel). It also determines strategic focuses analyzing the relationship between the share of voice on the air (SOV) and the share of the market (SOM). To achieve SOM growth, SOV must be greater than SOM, and vice versa; if SOV < SOM, the brand will lose ground. However, depending on the category and market segment, there is a different correlation between SOV and SOM. Thus, it is necessary to build a model of the influence of SOV on SOM based on the data of all brands of the category for several years and, based on it, determine the necessary effective SOV (ESOV) to achieve the business goals. In addition, the agent's task is to calculate the Media Rating indicator, which rates the change over a certain period of SOV and SOM, taking into account the brand's position:

$$Media\ Rating = \frac{\Delta SOM}{\Delta SOV} \cdot \frac{SOM}{Average\ SOM\ in\ the\ category}. \quad (6)$$

Since various functions in the proposed multi-agent MDSS are distributed among intelligent agents, most can work autonomously and asynchronously. Moreover, the interaction between agents allows for keeping the system up-to-date and quickly adapting to all marketing environment changes.

3. DISCUSSION

The key milestones of this analysis are forming the functional requirements for an MDSS and necessary intellectual agents, system development, and implementation into the marketing activity. As a realization of the proposed architecture of the MDSS for brand management, it is relevant to use interactive dashboards (Nadj et al., 2020) or develop separate software products. Here users that make marketing decisions can interact with the system, changing the planned indicators of marketing mix elements and factors of the marketing environment, and have an opportunity to change the setting of the constructed models. It should be noted that a final information system for supporting marketing decision-making does not necessarily contain all the components described above (Kingsman & de Souza, 1997). This study offers a description of the broadest possible version of filling the system. In practice, certain nodes can be replaced by ready-made solutions. For example, monitoring agents can be replaced by products of Proxima Research, Nielsen, GFK, or other systems.

Before building the multi-agent MDSS, it is worth assessing how functional each component will be in one way or another, taking into account the costs of its implementation and the expected improvement in the quality of decision-making with the help of the system (Juan et al., 2010). Therefore,

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to build an MDSS for the enterprise, it is advisable to apply the concept of building a flexible information and analytical system, which will make it possible to increase the efficiency of its operation (Lamb et al., 2012).

The proposed MDSS allows for achieving business goals most efficiently due to increasing the speed and quality of decision-making for the enterprises. Globalization and Data Science in marketing led to the unification and emergence of similar approaches to solving typical business problems, so the results can be used to further develop MDSSs and mathematical methodology in marketing, as well as to solve current problems of the global market.

The limitations of the current study are that the proposed MDSS only covers some possible agents for solving a wide range of marketing tasks for brand management. So, the future research strategy and its directions include overcoming the limitations of the current study for improvement of an MDSS's functionality, which contains the possibility to include additional agents to the system, for example, agents of regional analysis and modeling, agents for NLP processing of social listening (Chornous & Iarmolenko, 2017) or agents for analysis of market basket. This will help to find new hidden insights that help to develop new effective solutions and improve business results.

CONCLUSION

This study presents the architecture of the multi-agent MDSS that provides decision-makers with a set of interactive reports for brand management. Such an MDSS is based on Data Science tools and combines information and data on factors of the internal and external environment, media activity in various communication channels, and the dynamics of business indicators. Moreover, it includes intelligent agents (marketing mix modeling agent, price policy support agent, brand portfolio management agent, agent of strategic analysis, customer segmentation agent, customer classification agent, and forecasting agent). Its implementation allows to support main marketing decision-making processes and solves many tasks of marketing and communication activity. These tasks include: forming a marketing mix, optimizing the price index, improving the marketing budget allocation for a portfolio of brands and products, clarifying the media mix of advertising communications, assessing the influence and dangers from competitors, and, as a result, forecasting key business indicators. Customer analysis and marketing information systems based on Data Science methodology are essential for managing the enterprise and supporting the formation of marketing strategy and marketing decisions.

The proposed MDSS is easy to implement in the interactive dashboard or separate software format with a specific set of relevant agents, as various functions in it are distributed among intelligent agents, and most of them can work autonomously and asynchronously. Therefore, decision-makers can interact with the system or with necessary agents to quickly adapt to all changes in the marketing environment and effectively solve marketing tasks.

As a part of the model support of the MDSS, a methodology for developing economic-mathematical models based on Data Science tools was proposed, which makes it possible to optimize various aspects of marketing activities, in particular, the formation of an effective marketing strategy in general and its elements, solving the problems of attracting new and retaining current customers. Data Science shows the highest correspondence to modern marketing, where consumers, their behavior, and their response to marketing activity are the focus of enterprises. Therefore, the research findings provide a scientific basis for making effective marketing decisions based on data. The proposed MDSS can become part of an intelligent system for planning marketing activities.

AUTHOR CONTRIBUTIONS

Conceptualization: Galyna Chornous, Yana Fareniuk, Vincentas Rolandas Giedraitis.
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Investigation: Yana Fareniuk.
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Resources: Galyna Chornous, Yana Fareniuk.
Supervision: Galyna Chornous, Vincentas Rolandas Giedraitis.
Validation: Galyna Chornous, Yana Fareniuk, Erstida Ulvidienė, Ganna Kharlamova.
Visualization: Yana Fareniuk.
Writing – original draft: Galyna Chornous, Yana Fareniuk.
Writing – review & editing: Galyna Chornous, Yana Fareniuk, Vincentas Rolandas Giedraitis, Erstida Ulvidienė, Ganna Kharlamova.

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