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AUTOMATION OF PRICING MANAGEMENT IN RETAIL BASED ON DATA ANALYTICS

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Abstract:
This article examines the changing processes of pricing management in retail trade under the influence of digital transformation and the growth of data volumes. The potential of using data analytics and intelligent algorithms for automating pricing decisions is investigated. Pricing models are analyzed, including heuristic rules, regression methods, and machine learning algorithms, particularly reinforcement learning. Particular attention is given to the technological infrastructure that enables the integration of data sources and the implementation of pricing strategies in real time. The effects of introducing analytical tools are identified, including increased margin, accelerated inventory turnover, and improved adaptability of companies under market volatility.

JEL: L81, M31, C61

Keywords: dynamic pricing, automation, data analytics, machine learning, pricing algorithms, digital transformation

1. Introduction

Modern retail operates under conditions of intense competition, unstable consumer demand, and rapid proliferation of digital technologies. Traditional approaches to pricing, based on periodic market analysis and manual adjustments, are no longer sufficient to ensure the required speed of response and decision-making accuracy. In the digital economy, automation of this process is becoming an essential factor in improving management efficiency and achieving strategic business goals.

One of the most promising directions in this field is the use of data analytics tools to process large volumes of information on demand, competitor prices, inventory levels, and customer behavioral characteristics. The application of dynamic pricing (DP) algorithms enables the transition from static strategies to adaptive models capable of

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responding to market changes in real time and generating pricing decisions aimed at increasing profitability and maintaining customer retention.

The relevance of implementing intelligent pricing systems is driven by the need to enhance profitability and competitiveness under conditions of digital transformation (DT). The aim of this study is to analyze the potential of data analytics as a tool for automating pricing management in retail.

2. Main part. Theoretical foundations of pricing management automation

The concept of DP has emerged as a response to the increasing complexity of market processes and growing competition in the context of DT. While traditional methods relied on fixed price lists and infrequent adjustments based on seasonal fluctuations or cost changes, such approaches have become insufficient in modern retail. Market saturation, the growing share of online sales, and high consumer price sensitivity necessitate the transition to more flexible models. In this regard, DP is increasingly viewed as a strategic management tool that enables real-time consideration of demand fluctuations, competitor behavior, and inventory levels (fig. 1).

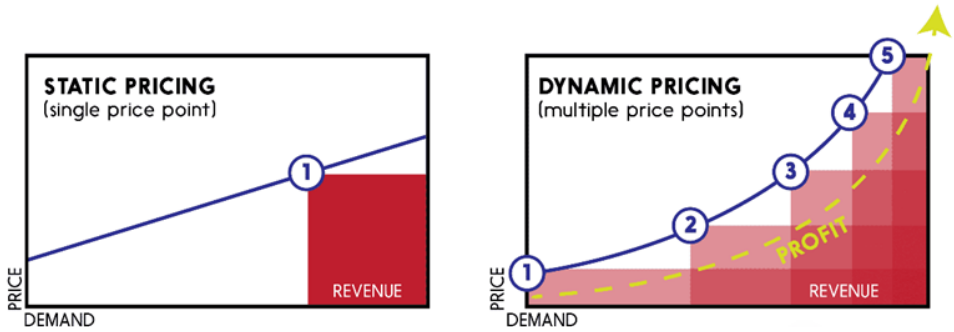

Figure 1: Comparison of static pricing and DP

A fundamental element in the development of this concept is the integration of data analytics, which has transformed the pricing process from a static and reactive model to an adaptive and proactive one. Analytical methods enable the construction of predictive models that account for demand elasticity and complex interdependencies between external and internal factors. This makes it possible to apply machine learning (ML) algorithms capable of identifying hidden patterns and automatically adjusting prices in response to changing conditions. Recent American studies confirm the effectiveness of this approach. In particular, research on pricing in online retail has shown that reinforcement learning makes it possible to develop more reliable strategies compared to classical regression models, ensuring revenue growth and increasing the accuracy of demand forecasts [1]. At the same time, practical experience from USA retail chains demonstrates that the implementation of electronic shelf labels and real-time price adjustment systems enhances management flexibility, though it requires regulatory oversight, as reflected in legislative initiatives in several states [2].

Thus, a deeper understanding of DP involves not only identifying its potential but also analyzing the models that underpin the automation of pricing management processes. Examining their characteristics and limitations helps trace the evolution of approaches and better understand future development directions in the context of the digital economy (table 1).

Table 1: Pricing models [3, 4]

Model	Main features	Limitations
Heuristic rules	Simple solutions based on fixed rules, such as discounts for excess inventory or price increases when demand increases.	Simplified reflection of market processes, lack of forecasting opportunities.
Regression models	Statistical assessment of the dependence of demand on price, seasonality and competition; working with historical data.	Limited ability to account for nonlinear effects and sudden fluctuations; high sensitivity to the quality of the source data.
Optimization algorithms	Maximizing profit or revenue under specified constraints, integration with inventory management and logistics.	Significant computational complexity, the need for constant updating of parameters.
Model	**Main features**	**Limitations**
ML	The use of classification and forecasting algorithms, the identification of hidden patterns, high accuracy.	The risk of overfitting, the difficulty of interpreting solutions, dependence on large amounts of data.
Reinforcement learning	The ability to adapt to changes in real time, correcting decisions based on the reaction of the environment.	Instability in the early stages, opacity of work, high resource requirements.

The comparison of models shows that the evolution of approaches is moving from simple rules toward adaptive systems. However, none of them is free from restrictions. Thus, despite the increasing efficiency of automated pricing, companies are forced to balance between technological capabilities and social risks associated with consumer perception of price adjustments and regulatory constraints. Consequently, a promising direction is the development of hybrid systems that combine the accuracy of predictive algorithms with the transparency and controllability of pricing decisions.

3. Algorithms digital transformation

The development of DP is impossible without the use of specialized algorithms that enable the processing of large volumes of information and the transformation of data into managerial decisions. Their application allows retailers to build adaptive strategies in which prices are not fixed values but the result of continuous market analysis.

One of the central directions is working with streaming demand data. In conditions of high transaction frequency and significant variability in consumer behavior, the ability of algorithms to process information in real time it becomes an important factor of efficiency. Modern systems combine time series methods, ML, and stream analytics, which makes it possible to detect short-term changes in demand and quickly reflect them in price adjustments.

Another essential component is the consideration of the competitive environment and price elasticity. Unlike static models, where price is determined by cost and markup, modern systems evaluate it in the context of competitive pressure and consumer response to price changes. Methods used to assess elasticity include regression models, Bayesian approaches, and neural network techniques.

Particular attention should be given to the use of data on inventory levels and logistical constraints. Algorithms DP are not limited to analyzing demand and competition; they also take into account operational parameters such as inventory turnover rates, delivery lead times, and storage costs. In the context of instability in global supply chains, this area has become especially relevant.

Finally, an important element of the algorithms is the prediction of consumer reactions. Modern systems go beyond the classical understanding of demand elasticity and incorporate behavioral models that account for the individual characteristics of customer decision-making [5]. Methods such as cognitive modeling, market basket analysis, and predictive analytics are applied to identify likely customer behavior scenarios in response to price changes.

The logic of the DP algorithm operation follows a sequential process. It includes several stages (fig. 2).

Figure 2: Stages of DP algorithm operation

Thus, these algorithms are not isolated statistical tools but integrated, comprehensive systems that combine the analysis of demand, competitive environment, logistical parameters, and behavioral factors. Their practical value lies in the ability not only to generate optimal pricing decisions but also to adjust them in real time. This provides companies with higher profit margins, faster inventory turnover, and strategic resilience under market volatility.

4. Technological infrastructure of automated systems

The development of effective DP systems is impossible without a reliable technological infrastructure that enables the collection, processing, and interpretation of data, as well as the automation of decision-making. In the context of retail DT, this infrastructure becomes an important factor in the successful implementation of intelligent pricing strategies.

One essential element is the integration of data sources. Modern systems rely on a wide range of information, including data from point-of-sale terminals, online sales channels, marketplaces, as well as external data on competitors and macroeconomic indicators. It is important to emphasize that the effectiveness of the system depends not so much on the data volumes themselves, but on their consistency and the ability to feed them into the analytical platform in a standardized format.

An equally important component is the architecture of analytical platforms. In recent years, the concept of end-to-end platforms has gained prominence, where business intelligence components provide visualization and interpretation of important metrics, ML tools enable the construction of predictive models for demand and elasticity, and Big Data technologies allow for real-time processing of streaming information. Thus, the architecture of the analytical system becomes a connecting link between disparate data flows and practical managerial actions.

The final element of the infrastructure is the automation of decision-making and the real-time implementation of pricing strategies. Modern algorithms go beyond generating recommendations and are directly integrated with pricing management systems, enabling automatic price adjustments in accordance with a company's target indicators [6]. This approach is especially important in conditions of high demand volatility, where delays between analytical signals and actual price changes may result in margin losses or reduced competitiveness.

Therefore, the technological infrastructure of automated pricing systems constitutes a multi-level framework. It is the combination of these elements that enables companies to transition from traditional static models to adaptive pricing systems, ensuring strategic resilience in the digital economy.

5. Effects of implementing data analytics in pricing management

The implementation of data analytics tools in pricing processes not only modernizes traditional approaches but also enables the development of new management models focused on increasing business efficiency. The impact of analytical technologies manifests in several areas, affecting both companies' financial performance and their strategic resilience in conditions of high market volatility.

First and foremost, such transformation directly influences profit margins and profitability. The use of data processing algorithms makes it possible to account for price elasticity of demand, competitive actions, and individual behavioral characteristics of consumers. As a result, price reductions for low-elasticity products are minimized, while prices for highly elastic categories are adjusted to stimulate demand without compromising profit.

Another important outcome of implementing data analytics is the improvement of inventory turnover. The use of predictive models enables more accurate demand forecasting and the development of dynamic promotion strategies, which reduces the likelihood of excess stock and minimizes the risk of product depreciation. Moreover, shortening the storage period of goods positively affects overall working capital and creates conditions for accelerating the turnover of financial resources, which is particularly important in the context of increasing competition and pressure on profitability.

The impact of analytics on a company's adaptability to market changes and its resilience is also of particular significance. In conditions of unstable demand, inflationary fluctuations, or external shocks, traditional pricing strategies often lack the necessary flexibility, resulting in profit losses or a decrease in market share. Data analytics, by contrast, allows for the modeling of various development scenarios and the creation of strategies capable of quickly adapting to changes in the external environment. Algorithms integrated with external data sources enable retailers to respond rapidly to competitor actions, shifts in consumer preferences, or disruptions in logistics. Thus, the analytical platform becomes a tool for strategic resilience, reducing the likelihood of critical losses in times of crisis.

These effects are not purely theoretical. They are confirmed by the practical experience of American companies. For instance, Kroger has automated regular price optimization and promotional effect evaluation using an analytical platform. Demand is modeled as a function of price and promotional activity, after which long-term pricing decisions are optimized based on this model. Causal validation is conducted through controlled displays and test stores using quasi-experimental methods. This approach reduces the cost of pricing errors and improves demand predictability over the planning horizon [7].

Another example is the experience of Home Depot, which implements artificial intelligence-based price optimization using the Revionics platform for product categories with a high level of product range complexity. This system enables scalable automation of pricing decisions in near real time. It enhances responsiveness to market changes and supports inventory levels within target thresholds [8].

Thus, the implementation of data analytics in pricing management has a multifaceted impact on retail operations. It contributes to increased margins and profitability, accelerates inventory turnover, and ensures strategic flexibility under conditions of uncertainty. Collectively, these effects provide a foundation for the transition to new management models, where analytics becomes not just a supporting tool but a core element of competitive strategy.

6. Conclusion

In the context of retail DT, pricing is no longer static but is evolving into a dynamic system based on the integration of data analytics, ML, and automated decision-making mechanisms. The application of intelligent algorithms leads to increased profit margins, accelerated inventory turnover, and enhanced strategic flexibility in conditions of market volatility. Technological infrastructure plays a critical role, incorporating the integration of heterogeneous data sources and the architecture of analytical platforms, which enables the deployment of adaptive models in real time.

Empirical examples confirm that the integration of analytical solutions into pricing strategies produces measurable effects, including cost reduction, improved forecast accuracy, and greater adaptability to changes in the external environment. Thus, analytics-based automation creates not only short-term financial benefits but also long-term competitive advantages.

Conflict of Interest Statement

The authors declare no conflicts of interest.

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