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ENSURING THE OBJECTIVITY OF THE TECHNOLOGY FOR FORECASTING BUSINESS PROCESS INDICATORS IN THE FIELD OF E-COMMERCE

The object of research is the technology of forecasting business process indicators in the field of e-commerce. These technologies were investigated to identify ways to increase their objectivity.

In the process of research, an analysis of input data was performed, time horizons were determined and expected results were formulated. Data normalization was carried out using the minmax method, anomaly detection was based on the standard deviation criterion. The choice of the forecasting method included the use of factual, expert and combined methods. Data processing was performed using the K-means and DBSCAN algorithms. Forecast formation was carried out using retrospective methods with the adjustment of indicators and activation functions. Monitoring and adjustment of forecasts was implemented through the MAPE, RMSE, MAE metrics and error analysis. The accuracy of forecasts was assessed by comparing methods by metrics in different scenarios, which ensured the adaptability of the model to a changing business environment. The proposed approaches integrate modern digital tools: big data analysis, automation of forecasting methods, anomaly processing, scenario approach and neural networks.

The objectivity of the technology for forecasting business process indicators in the field of e-commerce ensures increased forecast accuracy, adaptability to a changing market environment, and expands the possibilities for making strategic management decisions. This contributes to increasing the competitiveness of enterprises, their ability to quickly respond to changes in the market situation and improve management processes.

Due to increased objectivity of forecasting, enterprises can quickly respond to market changes and optimize resource use. The integration of modern data processing tools and multifactor metrics guarantees the accuracy of forecasts and takes into account complex relationships.

This creates a basis for strategic planning, ensures sustainable development of enterprises in the digital economy and allows for increased management efficiency in a dynamic market. The results of the study demonstrate that the adjusted technology for forecasting business process indicators in the field of e-commerce contributes to making informed management decisions focused on long-term effectiveness.

Keywords: *forecasting, e-commerce, integration of results, business management, anomaly detection, neural networks, decision optimization.*

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1. Introduction

The modern business environment is characterized by high dynamism, which necessitates the need for accurate forecasting of business processes. E-commerce, as one of the fastest growing areas, requires the use of innovative approaches to analysis and forecasting. According to forecasts, in 2025 the number of online buyers in the world will increase to 2.77 billion, which indicates the further development of e-commerce and the convenience of online shopping [1]. In Ukraine, the e-commerce market is also showing significant growth. Before the start of the full-scale war, the market volume increased annually, reaching 3.14 billion USD in 2021. Although in 2022 the market volume decreased to 300 million USD due to the war, in 2023 it recovered to 1.7 billion USD. In 2024, the volume of the e-commerce market in Ukraine exceeded 6 billion USD with an average annual growth rate of about 20 %, which indicates a rapid adaptation and recovery of the industry [2]. Traditional forecasting methods, focused on historical data and linear models, are increasingly becoming insufficiently effective in conditions of instability and complexity of markets. In addition, there is a problem of integrating large volumes of data of various types, such as macroeconomic indicators, financial indicators and digitalization indices, which complicates the formation of forecasts. Existing models often do not take into account anomalous events that can significantly affect the forecasting results. At the same time, promising methods, such as neural networks or combined algorithms, require significant computing resources and complex setup, which creates barriers to their implementation. The lack of a clear system for integrating forecasting results into business processes reduces the effectiveness of management decisions.

These problems require the development of new approaches to modeling that would ensure the accuracy of forecasts, take into account anomalies, adapt to environmental changes and could be integrated into real business scenarios. Thus, it is necessary to explore the possibilities of adjusting existing forecasting technologies, particularly in e-commerce, to increase their adaptability, accuracy, and compliance with modern requirements.

A critical analysis of the literature on business process forecasting technologies in the e-commerce sector allows to identify key approaches, models and methods used to achieve this goal. Thus, an intelligent business forecasting system based on the integration of statistical methods and artificial intelligence is an important basis for modern approaches, but requires adaptation to modern conditions and access to big data [3]. The way out of the situation is to use special forecasting software, which is formed taking into account the compliance of software tools with business needs [4]. This approach is useful, but does not sufficiently cover the specifics of e-commerce. Another promising vector of research in this area is the use of time series to develop e-commerce market forecasting systems, which demonstrates their effectiveness in short-term forecasts, but limits the possibilities for long-term forecasting [5]. In this context, considerable attention is paid to predicting customer churn and retention strategies in the B2B e-commerce segment using support vector machines [6]. This approach has practical value, but needs to be adapted to other market segments. It has been proven that overcoming a number of problems related to forecasting in the field of e-commerce is possible based on the combined ARIMA model with Google Trends data [7]. This innovative idea shows high potential, but dependence on external data may limit its application. This problem can be overcome by using a long-short-term memory (LSTM) neural network to forecast demand in e-commerce, demonstrating high accuracy. Despite this, this method requires significant computational resources [8]. A successful attempt to solve this problem is the development of a deep neural network for forecasting sales in e-commerce, which is effective for large amounts of data, but requires high qualifications for implementation [9]. The XGBoost technology for forecasting sales in cross-border e-commerce is distinguished by its speed and accuracy, but its application may be limited by the complexity of optimizing indicators [10]. Overcoming these and other limitations is important with the help of an intelligent approach to demand forecasting, based on the integration of various models [11]. This solution is quite promising, it demonstrates high potential, but requires a more detailed analysis of the results. The same applies to the use of machine learning to create a business forecasting system [12]. It has been proven that corporate business process management is important for integrating forecasting into the overall management system, but requires a more detailed coverage of e-commerce aspects [13], in particular, the impact of world events on e-commerce demand, taking into account anomalous events, and dependence on contextual data [14]. These and other limitations can be significantly reduced by using the FB-Prophet model for sales forecasting, but current research indicates that this technology requires adaptation to changing market conditions [15], in particular, a deep analysis of demand in e-commerce, which emphasizes the importance of big data, but leaves open the issue of integration with existing systems [16]. Current aspects of forecasting are the identification of vectors and dynamics of customer service systems and mentoring activities based on modeling, which is of high value for business process management [17–20]. With this in mind, a web-based ordering system with forecasting for startups has been developed, which demonstrates adaptability to small businesses [21]. In this context of research on forecasting models, it is appropriate to mention a demand forecasting system based on big data models, which provides a high level of detail, but depends on the availability of quality data [22]. The role of complex systems in predictive analytics for innovations in e-commerce remains relevant, expanding opportunities for strategic planning [23]. In general, the analysis shows that technologies for forecasting business process indicators in the e-commerce sector are developing rapidly. However, their implementation requires detailed adaptation to the specifics of e-commerce, data availability and resources.

The aim of research is to improve the technology for forecasting business process indicators in the e-commerce sector by formulating recommendations to increase its objectivity. To achieve this aim, a number of objectives were performed, namely:

– identification of stages of the technology for forecasting business process indicators in the e-commerce sector, taking into account trends in the digitalization of business processes;

– critical analysis and adjustment of the technology for forecasting business process indicators in the e-commerce sector, taking into account trends in the digitalization of business processes.

2. Materials and Methods

The research used a set of methods to perform key forecasting tasks in the field of e-commerce, which ensure the consistency, accuracy and practical feasibility of the results obtained. At the first stage, which consists in formalizing the forecasting goal, a functional structuring approach was used, which allows establishing relationships between input data, time horizon and expected results, which makes it possible to clearly define the logic of further analytical actions. At the stage of data collection and preliminary analysis, the minmax-normalization method was used to unify the scales of variables, which is especially important when using variables with different units of measurement, as well as the standard deviation criterion to detect anomalies, which allows cleaning the data from distortions that can distort the modeling results.

Two main methods were used to structure and analyze large volumes of data at the processing stage. The K-means clustering method allows to group data by similar characteristics, identify hidden patterns and prepare data for further analysis. The DBSCAN algorithm, in turn, is used to detect complex structures and at the same time to identify anomalies, which is critically important in the case of uneven data density or their non-standard nature. These approaches provide high-quality data preparation for modeling, increasing the reliability of forecasts.

In the process of forecasting, retrospective and prospective methods are used. Among retrospective methods, a key role is played by time series analysis, which allows building basic forecasts based on historical dynamics, taking into account trends, seasonal and random components. For this purpose, the stages of series decomposition, coefficient estimation and construction of a forecast equation are provided. A prospective method used in the text is neural networks, which allow modeling complex and nonlinear relationships between input data, ensuring high accuracy of forecasts even under conditions of multifactoriality and significant uncertainty. These methods implement different approaches to forecasting depending on the complexity of the data and the business environment in which they are used.

To ensure the practical value of the obtained forecasts, optimization models were used, in particular the linear programming problem, which allows, based on forecast data, to form the best option for resource allocation, taking into account the specified constraints. This approach allows developing justified decision-making scenarios and implementing forecasting results into real business processes.

In order to increase the accuracy of forecasting and adapt models to changing conditions, error estimation methods were used, in particular MAPE and RMSE. MAPE was used to determine the average relative error, which allows comparing models with each other regardless of the data scale, while RMSE is more sensitive to large deviations and is better suited for tasks where taking into account the accuracy of values is critically important. Both metrics provide a deep assessment of the effectiveness of models and contribute to their further adjustment.

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Therefore, the consistent application of normalization methods, anomaly detection, clustering, time series analysis, neural networks, linear programming, and accuracy assessment metrics allows to build a comprehensive forecasting system that takes into account the peculiarities of the business environment, the complexity of input data, and the need to make effective management decisions.

3. Results and Discussion

3.1. Identification of stages of technology for forecasting business process indicators in the e-commerce sector, taking into account trends in business process digitalization

Taking into account positions [1–23], stages of technology for forecasting enterprise financial management systems in the context of trends in business process digitalization in the e-commerce sector are proposed (Fig. 1).

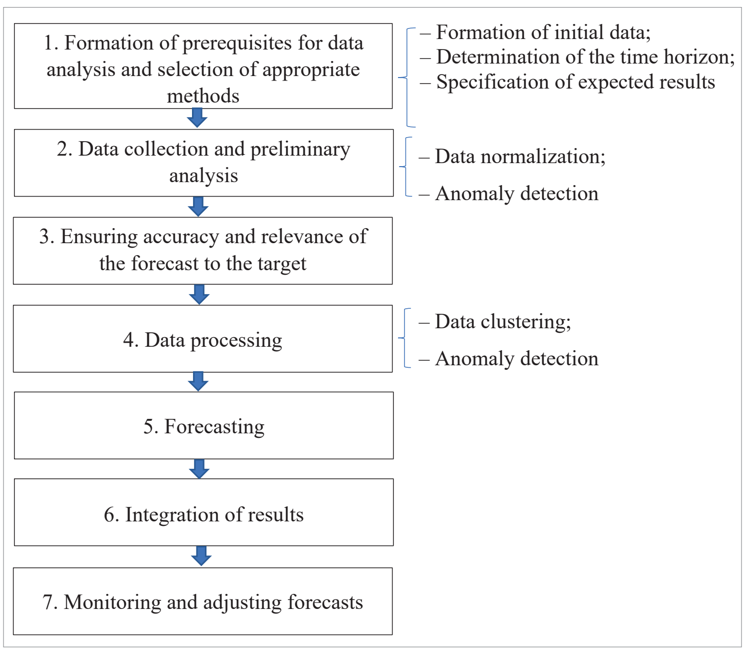

Fig. 1. Stages of the technology of forecasting of enterprise financial management systems in the context of trends in the digitalization of business processes in the field of e-commerce

Within the framework of this research, forecasting is understood not as the isolated use of a separate method or model, but as a holistic organizational and analytical system that covers all stages of data transformation for making management decisions. The term "forecasting technology" used covers a logically structured set of stages, tools and solutions that are implemented sequentially and interrelatedly. Unlike a method that answers the question "how" forecasting is carried out, or a model that formalizes the relationships between variables, technology describes the entire trajectory of the process: from goal formation, data collection and cleaning, to a reasoned choice of tools, forecast generation, its optimization interpretation and integration into the decision-making system. In confirmation of this, it is worth emphasizing that, in this case, it is not only about the forecast construction algorithm, but also about the sequence of operations that ensure its life cycle: big data processing, anomaly detection, clustering, selection of a forecast approach, scenario modeling, automated real-time model adjustment, multi-criteria assessment of forecast accuracy and monitoring of their effectiveness. Such integration of tools into a process with a defined logic and relationships between stages corresponds to the essence of technology as an applied knowledge system that is implemented in a specific functional environment. A forecasting model or method is not a self-sufficient element, but is a component of technology as a functional scheme with a full life cycle, focused on practical implementation in business systems that require constant adaptation, scaling, and integration with other management tools.

The sequence of stages of the technology allows enterprises to effectively adapt to digital transformations, integrate forecasts into their activities and make informed management decisions. Each of the selected stages of the technology is considered in a formalized form.

Thus, when forming the prerequisites for data analysis and choosing appropriate methods, the main thing is to choose the goal (M) of the forecast, which structures the forecasting process, determining the relationships between input data, time horizon and desired results.

It can be represented as a function:

$$M = f(X, T, E),$$

where X – the input data, which is a fundamental component of forecasting, since they determine the basis for analysis and modeling. X includes: historical financial indicators (income, expenses, profit, cash flows, etc. They provide a retrospective view that is used to extrapolate trends or identify patterns); digitalization indices (level of automation, investments in digital technologies, data processing speed. These indicators are important for understanding the impact of digital changes on the financial activities of the enterprise); macroeconomic and industry indicators (exchange rates, lending rates, market price dynamics. They take into account the external environment in which the enterprise operates). The data must be sufficiently accurate, representative and meet the purpose of the forecast;

T – time horizon, which determines the duration of the forecast and affects the choice of analysis methods: short-term horizon (up to 1 year) is focused on solving operational tasks, such as managing working capital, forecasting sales or cash flows. In this case, fast and accurate methods are used, for example, trend extrapolation or regression modeling; long-term horizon (over 1 year) is aimed at strategic planning, for example, assessing the effectiveness of investment projects or implementing digital solutions. Scenario analysis or neural networks are usually used here to take into account high uncertainty;

E – expected results that formulate the forecasting goal. They can be quantitative or qualitative depending on the task: quantitative results (forecasted amount of income, expenses or investments, reduction of digitalization costs, etc.); qualitative results (increased adaptability to market changes or reduction of risks through the implementation of digital technologies, etc.). A clear definition of expected results is critical for further assessment of the forecasting effectiveness.

Formalizing the goal through a function $M = f(X, T, E)$ allows to integrate all aspects of forecasting into a single structure. For example:

– if the input data (X) includes historical financial indicators, and the time horizon (T) is short-term, the expected results (E) can be presented in the form of improved working capital management;

– for a long-term horizon (T), where X includes digitalization indices, the results (E) can be formulated as the projected growth in revenues from digital investments in five years.

Thus, this stage sets the main vector for all subsequent steps of the algorithm, ensuring the consistency and compliance of the forecast with real business needs.

Data collection and preliminary analysis are accompanied by data collection and preliminary analysis, which is critically important for ensuring the correctness and reliability of the forecast, since the quality of the input data directly affects the modeling results.

This stage involves:

– *data normalization.* Data normalization is used to unify their scales, which is especially important if the forecast is based on variables with different units of measurement or value ranges. Minmax normalization formula:

$$X' = \frac{X - min(X)}{max(X) - min(X)}, \quad (1)$$

where X' – normalized data; X – initial values of the variable; $min(X)$ – minimum value of variable X; $max(X)$ – maximum value of variable X.

Normalization translates all values of variable X into the range [0; 1]. This simplifies work with data for machine learning, regression analysis, or clustering algorithms that are sensitive to differences in the scales of input variables. For example, financial indicators (millions of dollars) and digital indices (fractions of a unit or percentages) after normalization will be reduced to a common scale, which reduces model distortion;

– *anomaly detection.* Anomaly detection allows to identify data that is significantly different from others and can distort the results of the analysis. For this, the standard deviation criterion is used:

$$A = \{x_i \in X \| x_i - \mu | > k\sigma\}, \quad (2)$$

where x_i – variable value; μ – average value of all x_i; σ – standard deviation; k – coefficient (usually k=2 or k=3).

This criterion is based on the fact that in a normal distribution, most of the data (about 95 %) are within $\mu \pm 2\sigma$. Values outside these limits are considered anomalies. For example, a sharp increase in costs caused by an external factor can be identified as an anomaly and further investigated. The standard deviation is calculated using the formula:

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^2}, \quad (3)$$

where n – the number of observations.

Normalization ensures the accuracy of the model, especially when using machine learning algorithms that are sensitive to the scale of the data. In turn, anomaly detection allows to clean the data from distortions that can lead to incorrect forecasts. This is critically important for financial data, where anomalies are often the result of one-time events, for example, large investments or crises. The data prepared at this stage are the basis for further analysis and forecasting, ensuring the correctness of the results.

Ensuring the accuracy and compliance of the forecast with the goal. The forecasting method is chosen depending on the specifics of the data, the degree of their availability, the level of automation of processes and the tasks to be solved. To perform the tasks provided for by this stage, it is advisable to use:

– *factual methods* (accurate for stable conditions, but require high-quality historical data);

– *expert methods* (useful in the absence of data, but may be subjective);

– *combined methods* (provide a balance between objectivity and flexibility, which makes them a universal tool in unstable conditions).

The choice of a forecasting method depends on the tasks and conditions, as well as the availability of data and the capabilities of the enterprise.

The data processing stage allows to structure, segment and identify hidden patterns in large data sets. For this, clustering and anomaly detection methods are used. So:

– clustering can be performed by various methods, for example, the K-means method for grouping data into k clusters. This algorithm minimizes the distance between points within one cluster and the center of this cluster. The advantages of the K-means method are simplicity of implementation, high speed of operation for small amounts of data. In turn, its disadvantages are: the need for a preliminary selection of k; sensitivity to the initial values of the cluster centers; poor efficiency for data with uneven density or complex structures;

– anomaly detection based on the DBSCAN algorithm (Density-Based Spatial Clustering of Applications with Noise) is used to detect clusters in data with complex structures and to identify anomalies (points that do not belong to any cluster). The main concept is the analysis of the density of points in space. The key indicators of the DBSCAN algorithm are: the radius (ϵ), within which points (x) are considered neighbors; as well as the minimum number of neighbors (MinPts), which is necessary for point x to be considered a core. The application of the DBSCAN algorithm involves:

1. For each point x, the number of neighbors within a certain radius is determined. If this number is MinPts, then the point x is a core.

2. All neighboring points within a certain radius from the core form a cluster.

3. Points that do not belong to any cluster are considered anomalies (noise). The DBSCAN algorithm is distinguished by its efficiency when working with data of uneven density and the ability to automatically detect anomalies. However, its disadvantages include the need for preliminary data analysis to select the ϵ and MinPts indicators, as well as sensitivity to variable scaling, which requires normalization. In this context, the K-means method is appropriate for classifying data into groups with similar characteristics, contributing to the study of patterns in data sets. In contrast, the DBSCAN algorithm is more effective for working with complex structures, allowing to simultaneously find clusters and identify anomalies, which makes it indispensable in certain data analysis tasks.

Both methods are powerful tools for pre-processing data, allowing to make them more structured for further forecasting.

At the stage of forecasting, mathematical models are used to predict future values of indicators. It includes the use of retrospective methods for analyzing historical data and prospective methods for building forecasts taking into account complex relationships.

Among retrospective methods, it is advisable to highlight time series analysis, which allows to predict future values of a variable based on its historical dynamics. The technology is described by the equation:

$$y_t = \alpha + \beta t + \epsilon_t, \quad (4)$$

where y_t – the value of the indicator at a point in time (for example, profit, sales volume); α – a constant that reflects the average value at t=0; β – a coefficient that characterizes the trend (growth or decline of the indicator over time); ϵ_t – a random error that takes into account the influence of uncontrolled factors.

The process of analysis based on the time series method involves the following stages:

– *decomposition of the time series.* The time series is decomposed into components: trend T_t – takes into account the general trend (growth or decline); seasonality S_t – takes into account recurring fluctuations; random component ϵ_t – models noise. In formal form, let's write this as follows:

$$y_t = T_t + S_t + \epsilon_t; \quad (5)$$

– *evaluation of indicators* α *and* β. The indicators of the model are estimated by the least squares method:

$$\beta = \frac{\sum_{t=1}^{n}(t - \bar{t})(y_t - \bar{y})}{\sum_{t=1}^{n}(t - \bar{t})^2}, \quad (6)$$

$$\alpha = \bar{y} - \beta\bar{t}, \quad (7)$$

where $\bar{y}$ and $\bar{t}$ – the average values of i and t, respectively;

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– *forecasting*. Based on the obtained values of the indicators, the technology uses the value of t to predict y_t. To perform forecasting tasks, it is possible to use the time series method or the neural network method.

The advantages of the time series method are ease of implementation and efficiency for stable environments with a clearly defined trend. The disadvantages include unsuitability for complex and irregular data, as well as ignoring the influence of additional variables, for example, macroeconomic factors.

The method of forming neural networks is one of the promising ones. This method involves the use of nonlinear relationships between input data. Forecasting based on neural networks has a number of significant advantages, among which the ability to work with large and complex data, as well as efficiency in identifying nonlinear and multifactorial relationships, is especially notable. However, such approaches also have certain disadvantages, in particular, the need for large amounts of data for training, complexity of setup, and high computational intensity. Compared to other forecasting methods, retrospective approaches are simpler to implement and interpret, but are limited in effectiveness in a stable environment with clear trends. In contrast, forward-looking methods, such as neural networks, demonstrate versatility by taking into account complex factors and nonlinear relationships, although they require significantly more resources for their implementation. In complex forecasting conditions, forward-looking methods, such as neural networks, provide higher accuracy, while retrospective methods are useful for analyzing past trends and creating basic forecasts.

The stage of integrating results is the final stage in the forecasting process and involves using the obtained results to make decisions in real business scenarios. The main emphasis should be placed on the optimal use of resources, taking into account the constraints and target indicators of the enterprise. The optimization model allows to form the best allocation of resources to achieve maximum effect.

The optimization model is formed in the form of a linear programming problem:

$$\arg max_x \sum_{i=1}^{n} c_i x_i \text{ provided } \sum_{i=1}^{n} a_i x_i \le b, \tag{8}$$

where x_i – the amount of resource used for the i-th process or task; c_i – the benefit (utility) obtained from using a unit of resource; a_i – the resource cost per unit of performance of the i-th task; b – the total available resource volume.

In this model, the objective function task is to maximize the total benefit $\sum_{i=1}^{n} c_i x_i$, which reflects the economic effect, for example, profit, productivity or cost reduction. The total resource costs $\left(\sum_{i=1}^{n} a_i x_i\right)$ should not exceed the available volume (b).

The main stages of integrating the results:

– *data preparation for optimization*. The forecast results (for example, expected demand, costs, profitability) are used to determine the indicators c_i, a_i and b;

– *scenario formation*. Various scenarios can be developed based on the forecasts: optimistic (increased benefit ci under favorable conditions); pessimistic (resource limitation b due to external risks); baseline (forecast values without significant changes);

– *solution of the optimization problem*. The problem is solved using linear programming methods, for example, the simplex method or using specialized software (Excel Solver, Python SciPy, MATLAB);

– *solution verification*. It is checked whether the resulting solution meets real business constraints and whether it achieves the specified goals;

– *integration into business process management*. The optimization results are implemented in the form of action plans. For example, budget allocation between departments, selection of projects for investment, etc.

The optimization approach has a number of advantages that ensure its effectiveness in decision-making. First of all, it contributes to the efficient use of resources, which allows achieving maximum benefits even under existing constraints. Thanks to the use of mathematical models, the decision-making process becomes objective, eliminating the influence of subjective factors. In addition, the optimization approach is flexible, as it allows to model various scenarios to find the best solutions.

Along with this, the effectiveness of this approach largely depends on the accuracy of the input data, in particular the forecasts of the indicators c_i, a_i and b. In real conditions, additional nonlinear constraints are possible, which can significantly complicate the task, which requires taking into account these factors for the successful use of the method.

Integration of forecasting results through optimization models ensures maximum resource efficiency, allows the enterprise to adapt to changes and make informed management decisions. This approach is universal and can be used in various industries for financial planning, production management, investment or logistics optimization.

Monitoring and adjusting forecasts ensures a permanent increase in forecasting accuracy and adaptation of models to changing conditions. The purpose of this stage is to identify discrepancies between actual and forecasted values, analyze errors and adjust models accordingly.

It is advisable to assess the accuracy of forecasts based on the MAPE (Mean Absolute Percentage Error) method. It is based on the definition of the mean absolute error:

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \cdot 100\% , \tag{9}$$

where y_i – the actual value of the indicator at time i; $\hat{y}_i$ – the predicted value of the indicator; n – the number of predicted values.

One of the advantages of this method is its flexibility, as it is convenient for analyzing data with different units of measurement. This is ensured by the normalization of errors relative to actual values, which makes MAPE a universal method for various areas of application. At the same time, the MAPE method has its limitations. It is sensitive to zero values of actual indicators, which can create problems during calculations. In addition, MAPE favors models that underestimate actual values, since the relative deviations for such cases are smaller.

Monitoring the accuracy of forecasts using MAPE allows for effective evaluation of models, which, in turn, helps to improve the quality of forecasting. Constant analysis of errors and adaptation of models are critically important in a dynamic business environment, as this ensures the relevance and accuracy of management decisions in the field of e-commerce.

In the context of forecast monitoring, in particular, assessing their accuracy, in addition to the MAPE metric, RMSE (Root Mean Square Error) should also be taken into account. MAPE and RMSE are not direct alternatives, as they have different characteristics, advantages and limitations. Both metrics are used to assess forecast accuracy, but each of them is suitable for different situations depending on the specifics of the data and tasks. If MAPE is convenient for comparing models on datasets with different scales or units of measurement, then RMSE calculates the square root of the mean square error, which makes it more sensitive to large deviations. RMSE is well suited for tasks where it is important to take into account large errors, as it amplifies their impact on the final estimate. However, RMSE depends on the units of measurement and can be more difficult to interpret in the context of relative deviations. Thus, if there is a question of choosing between MAPE and RMSE, it depends on the specifics of the task. If a relative accuracy indicator is needed, MAPE will be the better choice. However, if large deviations are critical or data in the same units are used, RMSE may be more useful. Sometimes it is useful to combine these metrics to get a more complete picture of the accuracy of the forecast. The formula for calculating RMSE is:

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}, \qquad (10)$$

where y_i – the actual value of the variable at time and; $\hat{y}_i$ – the predicted value of the variable at time and; n – the number of observations.

RMSE is one of the key metrics for assessing the accuracy of forecasts. It allows to identify significant errors and compare different models, ensuring objectivity and accuracy of the analysis. Using RMSE in combination with other metrics, such as MAPE or MAE (a linear metric that gives equal weight to each error in calculating the mean. MAE measures the absolute error in units of the forecast data, while MAPE expresses it as a percentage, which allow to compare models for different datasets with different scales. For example, MAE does not take into account the relative scale of the error, while MAPE shows how much the model is wrong as a percentage of the actual values. However, MAPE has limitations in the case of zero or close to zero actual values, as it divides the error by the actual value, which can lead to very large or infinite results. MAE does not have this problem, as it operates on absolute values without relative scaling), allows to get a comprehensive assessment of forecasting performance and improve the quality of the models.

A critical analysis of the described technology for forecasting business process indicators in the field of e-commerce revealed a number of shortcomings and limitations that require attention to improve its effectiveness. In particular, the formulation of the goal and objectives is often not detailed enough, which complicates the selection of optimal methods and assessment criteria. Incompleteness of input data or their low quality, in particular missing values or noise, significantly affect the accuracy of forecasts, and their processing is time- and resource-consuming. There is also subjectivity in the choice of forecasting methods and their limited adaptability create risks, especially in a changing environment. The task is additionally complicated by the shortcomings of the approaches used, for example, the insensitivity of some methods to complex nonlinear relationships or the need for a significant amount of data for training. This leads to the fact that models often do not take into account the key features of modern business systems. Another challenge is the integration of the results with business process management practices, which do not always fully take into account the complex nature of real-world conditions, such as nonlinear dependencies or scenarios with high uncertainty. Estimating forecast accuracy through existing metrics also has its limitations: some metrics, such as RMSE, amplify the impact of large errors, while others, such as MAPE, may be less accurate for large-scale data.

In general, the algorithm requires further adjustment by implementing more flexible, adaptive, and comprehensive approaches that allow it to work effectively with different types of data and conditions. This will help increase the accuracy of forecasts and their practical value for making management decisions.

3.2. Critical analysis and adjustment of the technology for forecasting business process indicators in the e-commerce sector, taking into account the trends in the digitalization of business processes

Table 1 lists the general limitations of the described forecasting technology and possible ways to eliminate them.

A mathematical apparatus for adjusting forecasting technology is proposed:

1. *Automation of method selection.* Automation of forecasting method selection can be implemented through optimization of the accuracy criterion, for example, mean absolute error (MAPE) or root mean square error (RMSE), based on a set of available methods:

$$\arg min_{M_k}=\left(\frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i-\hat{y}_{i,k}}{y_i}\right|\cdot 100\%\right), \qquad (11)$$

where M_k – the set of forecasting methods $(k=1,2,\cdots,m)$; y_i – the actual value; $\hat{y}_{i,k}$ – the predicted value for the *k*-th method; *n* – the number of forecast points.

This formula minimizes the MAPE error for automatic selection of the best forecasting method.

2. *Formalization of the scenario approach.* The scenario approach can be formalized as a set of forecasts, where each forecast corresponds to its own scenario:

$$P_s=\left\{\hat{y}_{i,opt},\hat{y}_{i,base},\hat{y}_{i,pess}\right\}, \qquad (12)$$

where $\hat{y}_{i,opt}$ – the forecast for the optimistic scenario; $\hat{y}_{i,base}$ – the forecast for the baseline scenario; $\hat{y}_{i,pess}$ – the forecast for the pessimistic scenario.

The formula for forecasts in each scenario takes into account possible changes in input indicators *X*:

$$\hat{y}_{i,s}=f\left(X_{i,s}\right), \qquad (13)$$

where $s\in\left\{opt,base,pess\right\}$.

Table 1

Limitations of the described forecasting technology and ways to overcome them

General limitations	Suggestions for overcoming constraints
Resource-intensive. The technology requires significant time, computing power, and analytical resources, especially at the stages of data processing and forecasting	Automating method selection. Using machine learning algorithms to automatically select the most appropriate methods based on the type and quality of data
Sensitivity to data quality. Inaccurate or incomplete data can negatively affect the accuracy of forecasts, which is especially critical for unstable industries	Working with anomalies. Developing methods that not only remove anomalies but also use them to better understand changes in business processes
Complexity of setup. The effectiveness of the technology largely depends on the correct setup of the methods (selection of clustering indicators, determination of the number of clusters, neural network architecture, etc.)	Dynamic updating of models. Applying online learning and adaptive methods that take into account new data in real time
Failure to take into account environmental changes. The technology is focused on analyzing current and past data, but may not take into account sudden changes in the external environment	Incorporating a scenario approach. Developing forecasts for multiple scenarios (optimistic, baseline, pessimistic) for greater flexibility in decision-making
Lack of integrated scenario analysis. Most stages of the technology do not involve modeling multiple scenarios, which is important for management decisions in an uncertain environment	Integrating metrics. Using multiple metrics (RMSE, MAPE, MAE) to get a more complete picture of accuracy

Based on changes in input indicators, regular dynamic updating of models is necessary, for example, by using online training, where the model is adjusted after each new observation x_t, y_t:

$$\theta_{t+1} = \theta_t - \eta \frac{\partial L\left(y_t, f\left(x_t; \theta_t\right)\right)}{\partial \theta_t}, \tag{14}$$

where θ_t – the model performance at the t-th iteration; η – the learning rate; L – the loss function (for example, MSE or MAE (a metric for estimating the accuracy of forecasts that calculates the mean squared difference between the actual (y_i) and predicted ($\hat{y}_i$) values, emphasizing larger weights on large errors. MAE (Mean Absolute Error) is a simple, intuitive metric that estimates the average error in absolute values and provides stability in the presence of anomalies. MAE estimates the mean absolute error, while MSE emphasizes larger weights on large deviations through squared errors; MAE is more stable and less sensitive to anomalies, so it is chosen if a uniform error estimate is important)); $f\left(x_t; \theta_t\right)$ – the model forecast based on the performance θ_t.

This formula implements real-time adjustment of the model performance.

Integration of metrics involves their weighted combination:

$$Combined\ Error = w_1 \cdot RMSE + w_2 \cdot MAPE + w_3 \cdot MAE, \tag{15}$$

where w_1, w_2, w_3 – weighting factors ($w_1 + w_2 + w_3 = 1$); $MAPE$ (9); $RMSE$ (10); MAE:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left| y_i - \hat{y}_i \right|. \tag{16}$$

In the course of the calculations performed, it is possible to detect anomalies (by anomalies in this context let's mean values or observations in a data set that differ significantly from typical or expected values). They can arise due to technical errors, changing external conditions, or unaccounted factors affecting the data. For example, in the financial performance of a company, an anomaly can be a sharp increase in costs due to a one-time large investment, a significant increase in revenues due to the introduction of a successful digital product, or a decrease in productivity due to force majeure circumstances, such as a system failure or a natural disaster. More generally, anomalies are data that differ from the general trend or group. They can be formally identified using statistical criteria, for example, if the value exceeds the limits of several standard deviations from the mean. In the context of the proposed algorithm, anomalies are not removed, since they can carry important information about rare events or changes in the business environment. Instead, they are used to build additional predictors that take into account the impact of these events on the forecast. This approach can improve the accuracy of the model, especially in cases where anomalous values are recurring or have a long-term impact on business processes. It is not advisable to remove anomalies, but rather use them for modeling through the extreme value processing method:

$$z_i = \frac{x_i - \mu}{\sigma}, \tag{17}$$

where x_i – the variable value; μ – the mean value; σ is the standard deviation.

Anomalies $\left(\left|z_i\right| > k, \text{where } k = 2 \text{ or } 3\right)$ are used to create additional predictors that take into account their impact:

$$f_{adj}(x) = f(x) + \gamma z_i, \tag{18}$$

where γ – the weighting factor that regulates the impact of anomalies on the forecast.

So, let's integrate the proposed adjustments into the initial forecasting model:

1. Defining the goal and objectives of forecasting. Supplementing this stage by including a scenario approach (12).
2. Data collection and preliminary analysis. Instead of removing anomalies, let's add their analysis to create additional predictors (17).
3. Using anomalies in the model (18).
4. Selecting a forecasting method. The selection of a method is automated based on error optimization, for example, MAPE (9). This approach allows to automatically select a method that minimizes the error.
5. Data processing. Giving preference to dynamic updating of indicators and their clustering:
   – for clustering, the DBSCAN method is updated using adaptive MinPts values based on new data;
   – in case of model updating, let's assume the application of formula (12).
6. Formation of forecasts for each scenario:
   – optimistic scenario $\left(P_{opt}\right)$ – takes into account favorable conditions;
   – base scenario $\left(P_{base}\right)$ – forecast without additional changes;
   – pessimistic scenario $\left(P_{pess}\right)$ – takes into account possible risks.
7. Integration of results with business process management practice, in particular, it concerns the consideration of scenarios for optimization models. For example:

$$\arg max_x \sum_{i=1}^{n} c_{i,s} x_i \text{ provided } \sum_{i=1}^{n} a_{i,s} x_i \le b_s, \tag{19}$$

where s corresponds to the scenarios (*opt*, *base*, *pess*).

8. Monitoring and adjusting forecasts. Instead of using only one metric, let's add an integrated accuracy metric (15).
9. Evaluating the results, taking into account the error analysis for each scenario:

$$E_s = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_{i,s} - \hat{y}_{i,s}}{y_{i,s}} \right| \cdot 100\%, s \in \{opt, base, pess\}. \tag{20}$$

This allows to assess the accuracy of forecasts for different conditions and adapt the model to a specific scenario.

Integrating these adjustments into the initial algorithm increases its adaptability, accuracy and flexibility. New elements, such as automation of method selection, work with anomalies, scenario approach and combined metrics, provide greater compliance with real business needs and dynamic environmental conditions.

The logic of the relationships between all stages of modeling is built on the consistent transformation of source data into useful information for making management decisions. The initial stage is to determine the goal and objectives of forecasting, which sets the strategic direction of the entire process. Formalization of the goal through a function $M = f(X, T, E)$ provides an understanding of what data is needed, for what period the forecast is formed, and what results are expected. This forms the basis for further actions and determines which methods and approaches will be most appropriate. The second stage, data collection and their preliminary analysis, logically follows from the first, since to implement the forecasting goals it is necessary to have a high-quality information base. At this stage, data normalization, cleaning, and analysis ensure their suitability for modeling. Identifying anomalies and incorporating them into the model helps to avoid distortions in the results and increase the accuracy of forecasts. The next logical step is to choose a forecasting method based on the characteristics of the collected data and the formulated tasks. For example, if the data is stable and retrospective, factographic methods can be used, while in the case of high uncertainty, it is better to use expert or combined approaches. Automation of the method selection through error optimization ensures objectivity and adaptability to different conditions. The data processing stage logically continues the method selection, since it is at this stage that the data is structured, grouped (clustering) and prepared for the application of the model. For example, K-means clustering or DBSCAN allows to identify hidden patterns and segments that require a different approach to forecasting. This also creates the basis for adaptive models that are dynamically updated based on new data. After data processing, forecasts are generated. This is the stage at which the analysis results are converted into specific numerical values. The use of retrospective methods allows for the assessment of historical trends, while prospective methods, such as neural networks, take into account complex relationships and possible future changes. The formation of several forecasts in different scenarios (optimistic, baseline, pessimistic) increases the reliability of the results. The sixth stage, the integration of the results into business process management, ensures the practical implementation of the forecasts. Using optimization models, resources are allocated in such a way as to achieve maximum benefit under existing constraints. This ensures a close connection between the mathematical forecasting model and real management tasks. Monitoring and adjusting forecasts at the seventh stage allow for the assessment of the accuracy of the results obtained and, if necessary, make changes to the model. The use of metrics such as RMSE or combined errors helps to identify systemic shortcomings and adapt the forecasting to the changing environment. This provides feedback in the process, allowing for the forecasting to be made more accurate and relevant. The final stage – evaluation of the results, summarizes the entire process and provides an analytical basis for choosing the best methods and approaches in the future. Comparing the effectiveness of forecasting methods through metrics such as RMSE or MAPE allows to formalize conclusions and prepare recommendations for improving models in subsequent iterations.

All stages of the improved technology for forecasting business process indicators in the field of e-commerce are interconnected and constitute a holistic process, where each subsequent step is based on the results of the previous one, ensuring a gradual transition from primary data to valuable management decisions. Such a sequence minimizes errors, takes into account the specifics of the data and business environment, and also increases the reliability of forecasts.

Let's demonstrate the results of improving the primary technology based on empirical data from companies such as Rozetka, Prom.ua, Allo, Epicentrk.ua, Foxtrot (Table 2).

Table 2

Comparison of accuracy and adaptability of business process performance forecasting technology in e-commerce

Indicators	Rozetka	Prom.ua	Allo	Epicentrk.ua	Foxtrot
CM	0.12	0.11	0.06	0.04	0.07
MAE	0.10	0.11	0.08	0.13	0.12
MAPE	0.08	0.10	0.09	0.12	0.11
RMSE	0.12	0.15	0.11	0.14	0.13
Opt	0.08	0.09	0.07	0.10	0.09
Base	0.10	0.11	0.09	0.12	0.11
Pess	0.12	0.13	0.11	0.14	0.13

Table 2 shows the values of the main metrics (RMSE, MAPE, MAE) and their weighted combination, as well as the evaluation of the results taking into account the error analysis for the three scenarios. Thus, for the Rozetka company, the RMSE value is 0.12, MAPE is 0.08, and MAE is 0.10. The weighted combination of these metrics, taking into account the weighting factors, is 0.10. This indicates an average level of forecast error, which indicates the stability of the model. Scenario analysis for this company shows that in the optimistic scenario the error decreases to 0.08, in the base one it remains at 0.10, and in the pessimistic one it increases to 0.12. This indicates a high level of dependence of the forecast accuracy on external conditions. For Prom.ua, the RMSE is 0.15, the MAPE is 0.10, the MAE is 0.11, and the weighted combination is 0.12. These data indicate a slightly higher volatility of forecasts compared to Rozetka. In the scenario analysis, the error ranges from 0.09 in the optimistic scenario to 0.13 in the pessimistic one, with a baseline value of 0.11. Based on this, it can be argued that there is potential for reducing errors, provided that favorable factors are taken into account. Allo demonstrates the lowest MAE value among all participants – 0.08, which is a strong indicator of the model's effectiveness. The RMSE is 0.11, the MAPE is 0.09, and the weighted combination of metrics is 0.09. In the scenario analysis, the optimistic indicator reaches 0.07, the baseline – 0.09, and the pessimistic – 0.11. This emphasizes the stability of the company's forecasts, even under adverse conditions. In turn, Epicentrk.ua has an RMSE of 0.14, a MAPE of 0.12, and a MAE of 0.13, which indicates a slightly higher error in the modeling, compared to other companies. The weighted combination for this participant is 0.12. The errors in the scenarios vary from 0.10 in the optimistic scenario to 0.14 in the pessimistic one, which indicates a high dependence of the forecasts on external factors. And at the very end, Foxtrot demonstrates an average level of error with an RMSE of 0.13, a MAPE of 0.11, and a MAE of 0.12. The weighted combination of metrics is 0.11, which is the average for the sample. Scenario analysis shows that the optimistic error value is 0.09, the base value is 0.11, and the pessimistic value is 0.13. This confirms the potential for improving the accuracy of forecasts, provided that favorable circumstances are taken into account.

Thus, the analysis of the constructed diagrams allows to conclude about the accuracy of forecasts for each company and the dependence of these indicators on the scenarios of development of events. The most stable forecasts are demonstrated by Rozetka and Allo, which is confirmed by low error values and a small spread between scenarios. Epicentrk.ua and Prom.ua indicate the need for additional consideration of variable conditions to improve accuracy. In general, the weighted combination of metrics has proven itself as an effective tool for an integrated assessment of forecasts.

Table 3 presents curves reflecting the optimal solutions $\left(\arg max_x\right)$ for each company, as well as the significance of the impact of forecast accuracy on managerial decision-making within the optimistic, base, and pessimistic scenarios.

Table 3

Optimal solutions for each company, as well as the impact values for the optimistic, base and pessimistic scenarios

Indicators	Rozetka	Prom.ua	Allo	Epicentrk.ua	Foxtrot
Opt	0.92	0.88	0.95	0.85	0.89
Base	0.90	0.85	0.91	0.80	0.89
Pess	0.88	0.83	0.89	0.78	0.87

For Rozetka, the optimal solution is 0.92, which exceeds the baseline (0.90) and pessimistic (0.88) scenarios, highlighting the potential for risk reduction through investments in stability. In Prom.ua, the optimal solution (0.88) takes into account significant dependence on external conditions, suggesting adaptive strategies to reduce errors in the pessimistic scenario (0.83). Allo demonstrates the highest optimal indicator (0.95), which outperforms all scenarios and indicates effective resource management under conditions of high stability. Epicentrk.ua has an optimal solution at 0.85, which takes into account the wide spread between the pessimistic (0.78) and baseline scenarios (0.80), emphasizing the importance of scenario analysis for cost management. Foxtrot demonstrates stability between the optimal solution (0.89) and scenario impacts, allowing for effective resource planning even under adverse conditions.

The data in Table 3 illustrate how the optimization model based on contributes to the adoption of effective management decisions, taking into account various scenarios of events. This allows to increase the stability of the business and adaptability to external changes.

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The results obtained can be used to increase the accuracy of forecasting business process indicators in the field of e-commerce, which will contribute to improving the adoption of strategic management decisions. The integration of modern digital technologies allows to optimize costs, minimize risks and increase the competitiveness of enterprises. The use of the proposed forecasting model ensures effective resource management, which allows to reduce operating costs and increase the efficiency of business processes. In addition, the use of adaptive algorithms allows the business to quickly respond to changes in the market environment, which is critically important in unstable economic conditions. The adjusted forecasting technology can be applied in financial planning, inventory management, marketing research and analysis of consumer preferences, which contributes to the formation of a more flexible enterprise development strategy.

The main limitation is the need for high-quality input data, as insufficient accuracy or missing values can affect the forecast results. Lack of historical data or inaccuracies in statistical reports leads to significant deviations in forecasts. The use of complex machine learning algorithms requires significant computing resources, which can complicate their implementation in small and medium-sized enterprises that do not have a sufficient technical base. In addition, models using artificial intelligence require constant updating and adaptation to new data, which can cause additional costs. The study is focused on e-commerce, so its adaptation to other industries requires additional analysis of the features of the relevant business processes. The implementation of this model in more traditional business sectors requires modifications of the algorithms to take into account the specifics of a particular industry.

The conditions of martial law in Ukraine affected the conduct of the study due to limited access to current statistical data and the instability of the market environment. The war led to a change in consumer priorities and the transition of a significant part of business to the online segment, which required the adaptation of forecasting models to new conditions. In particular, the decrease in the purchasing power of the population and disruptions in logistics chains influenced the change in trends in the field of e-commerce, which complicates the accuracy of forecasts. Distance education and limited opportunities for conducting experimental research also made adjustments to the choice of methodological approach and analysis of the results obtained. In addition, legislative changes caused by martial law, such as temporary tax breaks or restrictions on foreign economic activity, create additional influencing factors that should be taken into account in forecasting models. It is also important to note that the instability of the infrastructure, disruptions in the operation of payment systems and failures in the supply of electricity can significantly affect the collection and processing of data, which complicates the implementation of automated solutions in the field of business process forecasting.

Further research should be conducted to expand the methodological base for integrating modern digital tools into predictive models of business process indicators. Particular attention should be paid to the development of adaptive algorithms that take into account complex relationships between data and allow integrating forecast results into real business scenarios in an unstable market environment.

4. Conclusions

The research results allowed to create a technology for forecasting business process indicators, focused on modern trends in their digitalization in the field of e-commerce. This technology covers all key stages of forecasting, starting from the formation of goals and objectives and ending with the integration of results into the practical activities of enterprises. The use of such a model ensures the integrity of the forecasting process, since it takes into account the specifics of the input data, the time horizon and the expected results. The involvement of qualitative data and their preliminary analysis allow to minimize errors and take into account external influences, which ensures the reliability of forecasts even in unstable conditions. The combination of various analysis methods – from factual to prospective – guarantees the flexibility and adaptability of the model, allowing it to be used to solve operational tasks and long-term strategic planning. The technology provides an effective combination of classical statistical approaches with modern machine learning methods, which allows to identify complex dependencies between indicators and accurately predict the impact of changes on financial results. The integration of forecasting results into business processes contributes to making informed decisions, optimizing resources and increasing overall management efficiency. A generalized approach to building a predictive model allows e-commerce enterprises to adapt it to their needs, which is critically important in the context of rapidly changing market environments. This contributes to increasing financial stability, as well as the formation of competitive advantages based on the effective use of digital technologies in management processes. Thus, the developed technology is a universal tool that provides e-commerce enterprises with the ability to flexibly respond to the challenges of digital transformation and effectively implement innovations in their activities. The optimization approach ensures effective decision-making in business systems due to the rational use of resources, objectivity of processes and the ability to model various scenarios. It allows to maximize benefits even with limited resources, integrating mathematical models into management processes. However, the effectiveness of this approach largely depends on the accuracy of input data and taking into account specific conditions, such as nonlinear constraints that can complicate the solution of problems. Integrating forecasting results through optimization models helps e-commerce companies adapt to changing conditions, ensuring informed management decisions in financial planning, investment, risk management, logistics, etc. Monitoring and adjusting forecasts, in particular using MAPE and RMSE metrics, make it possible to increase the accuracy of models and adapt them to a dynamic environment. MAPE is convenient for comparing models on datasets with different scales, while RMSE allows to take into account large deviations, which is important for high-risk tasks.

Along with the advantages of the optimization approach, its limitations are also highlighted, such as resource consumption, complexity of model tuning, and sensitivity to data quality. The use of a scenario approach, automation of method selection, and adaptive model tuning can be effective solutions to overcome these shortcomings. The inclusion of accuracy assessment metrics, such as MAE and integration of scenario analysis, helps to obtain a more complete picture of forecasting and increase its reliability. Therefore, the optimization approach is a powerful tool for resource management and decision-making in a complex business environment. Its versatility allows the proposed forecasting technology to be applied, ensuring flexibility, adaptability, and efficiency of management processes. However, to achieve maximum results, further automation, development of adaptive learning tools, and consideration of various scenarios of events are necessary. The proposed solutions for adjusting forecasting technology demonstrate an integrated approach to increasing the accuracy and adaptability of models, which is critically important in the modern business environment. Automation of the selection of forecasting methods ensures objectivity by minimizing the errors of the MAPE or RMSE metrics, which allows for optimal use of available methods for specific tasks. Integration of the scenario approach adds flexibility, as forecast modeling for optimistic, base and pessimistic scenarios allows e-commerce enterprises to prepare for various possible conditions and risks. An important component of the adjustment is working with anomalies, which are used to build additional predictors that take into account their impact on the forecast. This increases the relevance of models in cases where rare events can have a significant impact on business processes. Dynamic updating of models through online training ensures their relevance, allowing for real-time environmental changes. The combined use of metrics such as RMSE, MAPE and MAE contributes to a comprehensive assessment of the accuracy of forecasts and the selection of the most effective approaches. The inclusion of a weighted combination of these metrics ensures that various aspects of errors are taken into account, which allows improving the quality of forecasting even in difficult conditions. Integration of results into business processes through optimization models increases the efficiency of resource use and contributes to making informed management decisions. The formation of scenarios and their use in optimization tasks allows enterprises to adapt to changing conditions and maximize benefits even with limited resources. The logical structure of forecasting technology is built on a consistent transition from defining the goal and tasks of forecasting to evaluating results and forming recommendations. This approach ensures the consistency and reliability of the process, allowing for the integration of modern tools, taking into account the specifics of the business environment and adapting to dynamic changes. Improved forecasting technology creates a reliable basis for increasing management efficiency, contributing to the development of flexible and sustainable business models in modern conditions.

Conflict of interest

The authors declare that they have no conflict of interest regarding this study, including financial, personal, authorship or other, that could influence the study and its results presented in this article.

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Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the presented work.

References

1. *Kliuchovi tsyfry ta trendy e-commerce 2024* (2024). UA-Retail. Available at: https://ua-retail.com/2024/10/kliuchovi-tsyfry-ta-trendy-e-commerce-2024/?utm_source=chatgpt.com
2. Zakhozhyi, M. (2024). *Trendy ta vyklyky ukrainskoho rynku eCommerce u 2024 rotsi.* UAATEAM. Available at: https://uaateam.agency/blog/trendy-ta-vyklyky-ukrainskogo-rynku-ecommerce/?utm_source=chatgpt.com
3. Harrison, H. C., Qizhong, G. (1993). An intelligent business forecasting system. *Proceedings of the 1993 ACM Conference on Computer Science*, 229–236. https://doi.org/10.1145/170791.170834
4. Safavi, A. (2000). Choosing the right forecasting software and system. *The Journal of Business Forecasting Methods & Systems, 19 (3),* 6–10. Available at: https://typeset.io/papers/choosing-the-right-forecasting-software-and-system-5a5zfd2b5k
5. Fei-Fei, W. (2009). E-commerce market forecast system R&D based on time-series. *Information Sciences.* Available at: https://www.semanticscholar.org/paper/E-commerce-Market-Forecast-System-R%26D-Based-on-Fei-fei/db40ce09339277d57cf0052eacf37de1175fecc0?utm_source=consensus
6. Gordini, N., Veglio, V. (2017). Customers churn prediction and marketing retention strategies: An application of support vector machines based on the AUC parameter-selection technique in B2B e-commerce industry. *Industrial Marketing Management, 62,* 100–107. https://doi.org/10.1016/j.indmarman.2016.08.003
7. Carta, S., Medda, A., Pili, A., Recupero, D., Saia, R. (2018). Forecasting e-commerce products prices by combining an autoregressive integrated moving average (ARIMA) model and Google Trends data. *Future Internet, 11 (1),* 5. https://doi.org/10.3390/FI11010005
8. Bandara, K., Shi, P., Bergmeir, C., Hewamalage, H., Tran, Q., Seaman, B. (2019). Sales demand forecast in e-commerce using a long short-term memory neural network methodology. *Proceedings of the 26th International Conference on Neural Information Processing (ICONIP 2019), 11955,* 462–474. https://doi.org/10.1007/978-3-030-36718-3_39
9. Qi, Y., Li, C., Deng, H., Cai, M., Qi, Y., Deng, Y. (2019). A deep neural framework for sales forecasting in e-commerce. *Proceedings of the 28th ACM International Conference on Information and Knowledge Management,* 299–308. https://doi.org/10.1145/3357384.3357883
10. Ji, S., Wang, X., Zhao, W., Guo, D. (2019). An application of a three-stage XGBoost-based model to sales forecasting of a cross-border e-commerce enterprise. *Mathematical Problems in Engineering.* https://doi.org/10.1155/2019/8503252
11. Aal, S. (2020). An intelligent approach for demand forecasting in e-commerce. *American Journal of Business and Operations Research, 1 (2),* 77–83. https://doi.org/10.54216/ajbor.010203
12. Mia, M., Yousuf, M., Ghosh, R. (2021). Business forecasting system using machine learning approach. *2021 2nd International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST),* 314–318. https://doi.org/10.1109/ICREST51555.2021.9331114
13. Yaremko, S., Kuzmina, E., Savina, N., Yepifanova, I., Gordiichuk, H., Mussayeva, D. (2022). Forecasting business processes in the management system of the corporation. *Informatyka, Automatyka, Pomiary w Gospodarce i Ochronie Środowiska, 12 (4),* 51–55. https://doi.org/10.35784/iapgos.3249
14. Kalifa, D., Singer, U., Guy, I., Rosin, G. D., Radinsky, K. (2022). Leveraging world events to predict e-commerce consumer demand under anomaly. *Proceedings of the Fifteenth ACM International Conference on Web Search and Data Mining (WSDM '22),* 430–438. https://doi.org/10.1145/3488560.3498452
15. Bajoudah, A., Alsaidi, M., Alhindi, A. (2023). Time series forecasting model for e-commerce store sales using FB-Prophet. *14th International Conference on Information and Communication Systems (ICICS),* 1–6. https://doi.org/10.1109/ICICS60529.2023.10330530
16. Tang, T. (2023). Analysis and demand forecasting based on e-commerce data. *6th International Conference on Artificial Intelligence and Big Data (ICAIBD), 64–68.* https://doi.org/10.1109/ICAIBD57115.2023.10206072
17. Kucher, L., Kniaz, S., Heorhiadi, N., Tyrkalo, Y., Bovsunivska, A. (2023). Development of a customer service system in electronic commerce. *Business Management, 2 (20),* 64–82. https://doi.org/10.58861/tae.bm.2023.2.04
18. Kniaz, S., Brych, V., Heorhiadi, N., Shevchenko, S., Dzvonyk, R., Skrynkovskyy, R. (2024). Enhancing the informativeness of managing mentoring activities based on simulation modeling. *Proceedings of the 2024 14th International Conference on Advanced Computer Information Technologies (ACIT),* 384–388. https://doi.org/10.1109/ACIT62333.2024.10712547
19. Kniaz, S., Brych, V., Heorhiadi, N., Shevchenko, S., Dzvonyk, R., Skrynkovskyy, R. (2024). Informational-reflective management of mentoring activities development in the enterprise. *Proceedings of the 2024 14th International Conference on Advanced Computer Information Technologies (ACIT),* 389–392. https://doi.org/10.1109/ACIT62333.2024.10712601
20. Shpak, N., Seliuchenko, N., Dvulit, Z., Kniaz, S., Kucher, L. (2023). Assessment of the impact of macroeconomic crises and war on the activities of JSC "Ukrzaliznytsia". *Financial and Credit Activity Problems of Theory and Practice, 6 (53),* 260–272. https://doi.org/10.55643/fcaptp.6.53.2023.4177
21. Wiljohn, F., Prince, L., Marvile, S., John, E., Centeno, C. (2024). Web-based ordering system for start-up business with forecasting. *World Journal of Advanced Research and Reviews, 22 (3),* 357–368. https://doi.org/10.30574/wjarr.2024.22.3.1721
22. Nan, X., Wanting, S., Shaowen, Z., Daoyan, J., Yutong, W., Xiang, J. (2024). Intelligent prediction system of e-commerce commodity demand based on big data technology. *IEEE 4th International Conference on Electronic Communications, Internet of Things and Big Data (ICEIB),* 483–488. https://doi.org/10.1109/ICEIB61477.2024.10602621
23. Madanchian, M. (2024). The role of complex systems in predictive analytics for e-commerce innovations in business management. *Systems, 12 (10),* 415. https://doi.org/10.3390/systems12100415

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