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IMPROVING APPROACHES TO IDENTIFYING PROBLEM BUSINESS PROCESSES BASED ON THE BAYESIAN METHOD

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Abstract. In modern organizations, the complication of business processes and an increase in the amount of data make it difficult to make managerial decisions. Especially timely and accurate identification of problematic business processes is an important condition for improving the efficiency of the organization. Traditional deterministic and heuristic approaches do not show sufficient effectiveness in the face of uncertainty. In this article, the possibility of using the Bayesian probability method to improve approaches to identifying problem business processes is studied. The Bayesian method allows you to assess the problem probability of processes by combining a priori knowledge and observation data. The results of the study indicate a high level of flexibility and interpretation of the proposed approach. The proposed approach was tested on the basis of synthetic data and the ability to distinguish between problematic and normal business processes was evaluated. In the course of the study, a quantitative ranking of the risk level of processes was carried out by calculating aposteriory probabilities. The results obtained showed that the Bayesian model works stably in conditions of uncertainty compared to traditional methods. In addition, the interpretation of the results of the model allows us to support the management decision-making process. The presented method is suitable for practical application in systems for monitoring business processes and optimizing them.

Keywords: business processes, problem processes, Bayesian method, probability modeling, management decisions, risk assessment.

СОВЕРШЕНСТВОВАНИЕ ПОДХОДОВ К ВЫЯВЛЕНИЮ ПРОБЛЕМНЫХ БИЗНЕС-ПРОЦЕССОВ НА ОСНОВЕ БАЙЕСОВСКОГО МЕТОДА

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Аннотация. В современных организациях усложнение бизнес-процессов и увеличение объема данных затрудняют принятие управленческих решений. Особенно своевременное и точное выявление проблемных бизнес-процессов является важным условием повышения эффективности работы организации. Традиционные детерминистические и эвристические подходы не показывают достаточной эффективности в условиях неопределенности. В данной статье исследуется возможность использования байесовского вероятностного метода для совершенствования подходов к выявлению проблемных бизнес-процессов. Байесовский метод позволяет оценить вероятность проблемных процессов путем объединения априорных знаний и данных наблюдений. Результаты исследования свидетельствуют о высоком уровне гибкости и интерпретации предложенного подхода. Предложенный подход был протестирован на основе синтетических данных и была оценена способность различать проблемные и нормальные бизнес-процессы. В ходе исследования было проведено количественное ранжирование уровня риска процессов путем вычисления апостериорных вероятностей. Полученные результаты показали, что байесовская модель стабильно работает в условиях неопределенности по сравнению с традиционными методами. Кроме того, интерпретация результатов работы модели позволяет нам поддерживать процесс принятия управленческих решений. Представленный метод пригоден для практического применения в системах мониторинга бизнес-процессов и их оптимизации.

Ключевые слова: бизнес-процессы, проблемные процессы, Байесовский метод, вероятностное моделирование, управленческие решения, оценка рисков.

БАЙЕС ӘДІСІ НЕГІЗІНДЕ ПРОБЛЕМАЛЫҚ БИЗНЕС-ПРОЦЕСТЕРДІ АНЫҚТАУ ТӘСІЛДЕРІН ЖЕТІЛДІРУ

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Аңдатпа. Қазіргі ұйымдарда бизнес-процестердің күрделенуі және мәліметтер көлемінің ұлғаюы басқарушылық шешімдер қабылдауды қиындатады. Проблемалық бизнес-процестерді уақтылы және дәл анықтау ұйымның тиімділігін арттырудың маңызды шарты болып табылады. Дәстүрлі детерминистік және эвристикалық тәсілдер белгісіздік жағдайында жеткілікті тиімділікті көрсетпейді. Бұл мақалада проблемалық бизнес-процестерді анықтау тәсілдерін жетілдіру үшін байес ықтималдығының әдісін қолдану мүмкіндігі зерттелген. Байес әдісі априорлық білім мен бақылау деректерін біріктіру арқылы процестердің проблемалық ықтималдығын бағалауға мүмкіндік береді. Зерттеу нәтижелері икемділіктің жоғары деңгейін және ұсынылған тәсілді түсіндіруді көрсетеді. Ұсынылған тәсіл синтетикалық мәліметтер негізінде тексеріліп, проблемалық және қалыпты бизнес-процестерді ажырата білу қабілеті бағаланды. Зерттеу барысында апостериалдық ықтималдықтарды есептеу арқылы процестердің тәуекел деңгейінің сандық рейтингі жүргізілді. Алынған нәтижелер Байес моделінің дәстүрлі әдістермен салыстырғанда белгісіздік жағдайында тұрақты жұмыс істейтіндігін көрсетті. Сонымен қатар, модель нәтижелерін түсіндіру басқарушылық шешім қабылдау процесін қолдауға мүмкіндік береді. Ұсынылған әдіс бизнес-процестерді бақылау және оларды оңтайландыру жүйелерінде практикалық қолдануға жарамды.

Түйін сөздер: бизнес-процестер, проблемалық процестер, Байес әдісі, ықтималдылықты модельдеу, басқару шешімдері, тәуекелдерді бағалау.

Introduction. The competitiveness of organizations is directly related to the effectiveness of their business processes. Incorrect organization of business processes, inefficient allocation of resources, excessive time consumption and increased risks negatively affect the overall result of the organization's activities (Ahmad, et al., 2023:1-18). In this regard, the problem of identifying problem business processes and optimizing them is becoming increasingly relevant in the field of modern management and Information Systems (Pegoraro, 2022: 1-10). In most cases, the identification of problem processes is based on qualitative analysis, expert opinion or static indicators. However, such approaches provide insufficient accuracy in the face of uncertainty and data incompleteness

(Cheng&Sun,2022: 315-335). In real life, business processes are dynamic. They change under the influence of various external and internal factors. In this context, probabilistic approaches, especially the Bayesian method are considered as a promising tool in managerial analysis (Van der Aalst & Dustdar, 2023:689-704). The Bayesian method allows you to continuously update the initial (a priori) knowledge with new data. This creates the conditions for creating flexible and adaptive models in evaluating business processes (Radcliffe&Reklaitis, 2021:1377-1382).

The purpose of the study is to improve approaches to identifying problem business processes using the Bayesian method and justify its practical effectiveness.

The following scientific novelty of the research follows from the goal. It consists in developing a Bayesian model for identifying problematic business processes based on calculating a posteriori probabilities and quantifying the level of risk. The proposed approach provides an interpretable analysis of business processes in conditions of uncertainty and can be used to support management decision-making.

Nevertheless, the traditional methods used in the analysis and evaluation of business processes do not fully cover the complexity and multifactorial nature of processes. Especially complete lack of data, high noise and changes in processes over time negatively affect the accuracy of management decisions. In such a situation, static models cannot adequately reflect the real situation and do not allow timely identification of risks (Maleki Vishkaei, 2024: 755-774). In recent years, there has been a growing interest in data-driven and intelligent methods in Business Process Analysis. In this direction, approaches to machine learning, process mining and probability modeling are widely used (Van der Aalst, 2023:58-65). However, many machine learning models have "a black box" character, making it difficult to interpret the results obtained. This, in turn, can reduce confidence in the results of the model in the process of making managerial decisions (Rudin & Molnar, 2024:101-140).

In this context, the main advantage of the Bayesian method is its interpretability and ability to work in conditions of uncertainty. The Bayesian Probability model, combining a priori knowledge (expert opinion, historical data) with real observation data, makes it possible to quantify the probability that business processes are problematic. This approach is not limited to strictly classifying processes as "problematic" or "normal". Creates conditions for displaying the level of risk on the probability scale (Van der Aalst, et al., 2024: 227-256).

In addition, the Bayesian method allows you to dynamically monitor Business Processes and update estimates as new data is received. This property serves as the basis for considering it as an effective tool for solving the tasks of identifying problem business processes and optimizing them in a complex, changeable and uncertainty-filled organizational environment (Tiwari& Dumas, 2024: 1-24).

Literature review. Current research takes into account the complex and changeable nature of business processes. They require methods capable of modeling uncertainty in their analysis. In this context, Bayesian methods are being considered as a promising direction in identifying problematic business processes. The article (Prasidis, et al., 2021) recommends using Bayesian networks to manage the uncertainty that occurs during predictive business Process monitoring (e.g. result/next step/Time forecast). The authors combined the Directed Acyclic Graph (DAG) derived from the process model and the conditional probability tables (CPT) learned from the event log data to consider the prediction not only as a "result", but in conjunction with the probability/confidence level. As a result, this approach allows you to identify high-risk situations earlier and highlight cases that need to be monitored. In this work (Alman et al., 2022:102-133), the PN-BBN model combining Petri Net and Bayesian network is proposed, which is designed to identify anomalous behaviors in business processes. The proposed approach is proposed to describe the process structure using Petri Net. Allows you to estimate the probability of uncertainty and anomaly using the Bayesian network. The research (Ceravolo, et al., 2024:1-22) concept of predictive process monitoring is systematically considered. It is devoted to the main approaches to predicting the outcome, duration and next steps of business processes. The authors also note such pressing issues as data quality, interpretability, working with uncertainty. Provides future research directions. This article (Shimono, et al., 2025) discusses approaches to evaluating the performance of the Bayesian online changepoint detection method. The ability to accurately and promptly identify points of sharp changes in time data (changepoint) is analyzed. The method is also tested in a specific application scenario and shown to be effective in early detection of anomalies in dynamical systems. In this paper (Corneck, et al., 2025: 1-20) the online Bayesian changepoint detection method for network Poisson processes is proposed. The problem of determining the points of change in the intensity of events over time is considered. The proposed approach makes it possible to detect anomalies and structural changes in complex network systems in real time. In this research (Paape, et al., 2025: 29-52) a simulation-based optimization approach is considered to improve the performance of the production system. In order to effectively select parameters, the Bayesian Optimization (BayesOpt) method is used. The results of the study show that the BayesOpt approach is effective in increasing productivity indicators in complex production processes. This article (González&Zavala, 2024:446-451) presents the Bois (Bayesian Optimization of Interconnected Systems) method. The problem of effective optimization of complex systems, consisting of several interconnected systems, was studied. The authors use the Bayesian Optimization approach to take into account the dependencies between systems and show that there is an opportunity to increase overall performance. This paper (Sabbatella, et al., 2024:2232-2247) examines approaches to using the Bayesian Optimization method to optimize simulation-based systems. The authors indicate that this method allows you to find effective parameters with minimal testing in complex models, where computational resources are expensive. This article (Maitra, 2024) discusses the adaptive Bayesian Optimization algorithm. It aims to improve search efficiency by dynamically adapting model parameters in the optimization process. The proposed approach is proven to show faster and more stable results in complex and variable problems than traditional Bayesian Optimization methods. This research (Rauc, et al., 2024) presents the process-aware Bayesian Networks approach. It takes into account the sequence of events in the event log data. Therefore, it allows to analyze business processes from a probabilistic point of view. The proposed method is aimed at effective management of uncertainty in processes and explanatory identification of problem behaviors.

Materials and methods. The research used data-based probabilistic approaches to solve the problem of identifying problematic business processes. The analysis of business processes, the formation of synthetic data and the calculation of aposteriory probabilities using the Bayesian method were used as the basis. The proposed methods are aimed at formally assessing the level of problematization of processes in the face of uncertainty and supporting managerial decision-making.

3.1. Approaches to Business Process Analysis

The most common methods of Business Process Analysis include: Regulatory and functional analysis, indicator-based analysis (KPI), process map modeling (BPMN, IDEF0), risk-based analysis, etc.

Although these methods allow to describe the structure of processes, it is not always possible to quantify their problem. In this case, an analysis based on Bayesian methods shows good results.

3.2. Fundamentals of Bayesian method

The Bayesian method is based on probability theory and is characterized by the following basic formula:

$$P(A \mid B) = \frac{P(B \mid A) \cdot P(A)}{P(B)} \tag{1}$$

here

$P(A)$ is a priori probability;

$P(B)$ is the probability of an argument (evidence);

$P(B \mid A)$ - conditional probability;

$P(A \mid B)$ is the aposterior probability.

This method allows you to update the assessment every time new data is obtained.

3.3. Modeling problem processes by Bayesian method

In the proposed approach, each business process is in a certain state: problematic or normal. A priori, probability is determined on the basis of expert opinion or historical data. Indicators such as process time, costs, number of errors, inventory load are used as control data.

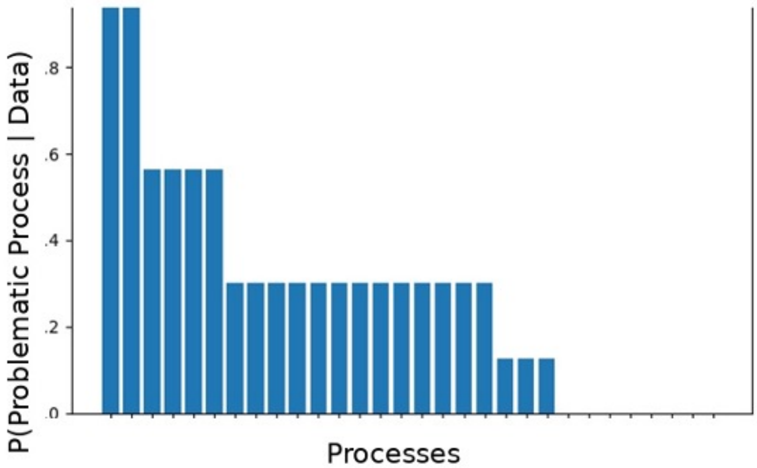

Figure 1. Aposteriory probability of a business process being problematic

In the course of the study, an artificial data set consisting of 30 business processes was created. Each process was characterized by the following indicators:

Process time (days) - Normal distribution

Cost increase coefficient-Normal distribution

Number of errors - Poisson distribution.

A priori probability:

$$P(\text{Problematic})=0.3$$

This value represents the hypothesis that, according to expert estimates, about 30% of the process in the organization may be in the risk zone.

3.4. Bayesian model

The aposterior probability for each process was calculated by the following formula:

$$P(A \mid B)=\frac{P(B \mid A) \cdot P(A)}{P(B \mid A) \cdot P(A)+P(B \mid \neg A) \cdot P(\neg A)} \tag{2}$$

here:

A - problem state of the process

$\neg A$ - the state of the process being "normal"

B - process indicators (time, cost, error)

$P(B \mid A)$ - the likelihood function, representing the probability of observing data B given that the process is problematic.

Methodology for calculating conditional probabilities: To determine $P(B \mid A)$ and $P(B \mid \neg A)$, we used probability density functions. For continuous indicators (Time, Cost), the Gaussian (Normal) distribution was used. For the discrete indicator (Number of Errors), the Poisson distribution was applied. The final likelihood is calculated as the product of the probabilities of individual indicators, assuming their conditional independence.

Conditional probabilities were calculated in weighted form depending on the deviation of the indicators from the norm.

Table 1. Aposteriory probabilities of business processes (fragment)

Process	Time (Days)	Cost ratio	Errors	P(problematic)
P26	5.13	1.28	1	1.000
P18	5.38	1.32	0	1.000
P3	5.78	1.00	4	0.563
P4	6.83	0.68	4	0.563
P21	6.76	1.10	3	0.563
…	…	…	…	…
P20	3.31	0.47	2	0.000
P22	4.73	0.88	1	0.000

Causal relationship of the results obtained:
0.6-1.0 range high risk
0.3-0.6 interval requires monitoring
0-0. 3 interval normal process.
To give the result in the form of a graph:

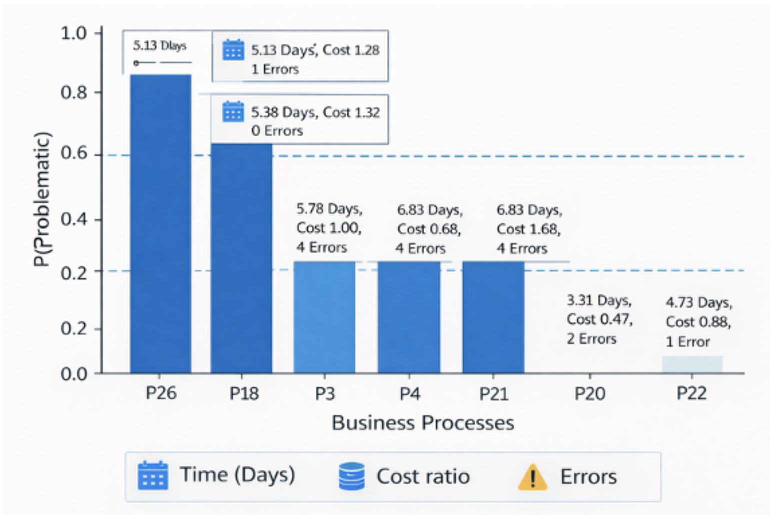

Figure 2. Aposteriory probabilities of business processes

This is calculated for each business process in the column chart.

$$P(\text{Problematic} \mid D) = \frac{P(D \mid \text{Problematic}) \cdot P(\text{Problematic})}{P(D \mid \text{Problematic}) \cdot P(\text{Problematic}) + P(D \mid \text{Normal}) \cdot P(\text{Normal})} \tag{3}$$

D - Control Data (time, cost, errors, etc.);
$P(\text{Problematic})$ - a priori probability;
$P(\text{Normal}) = 1 - P(\text{Problematic})$;
$P(D \mid \cdot)$ - conditional probability (likelihood).
Causal relationship of results:

For processes P26 and P18, $P = 1.0$. This is a very high risk and requires immediate optimization.

For processes P3, P4, and P21, $P \approx 0.56$. These processes need to be monitored, and additional analysis is recommended.

For processes P20 and P22, $P = 0$. These are normal processes that do not require intervention.

Horizontal dotted lines shown in the diagram (Figure 2):

0.3 - normal / control limit;

0.6 - control / high risk threshold.

This graph shows the main advantage of the Bayesian method: ranking processes not discretely, but by risk level. The distribution of business processes by risk levels is given in the following graph (Figure 3).

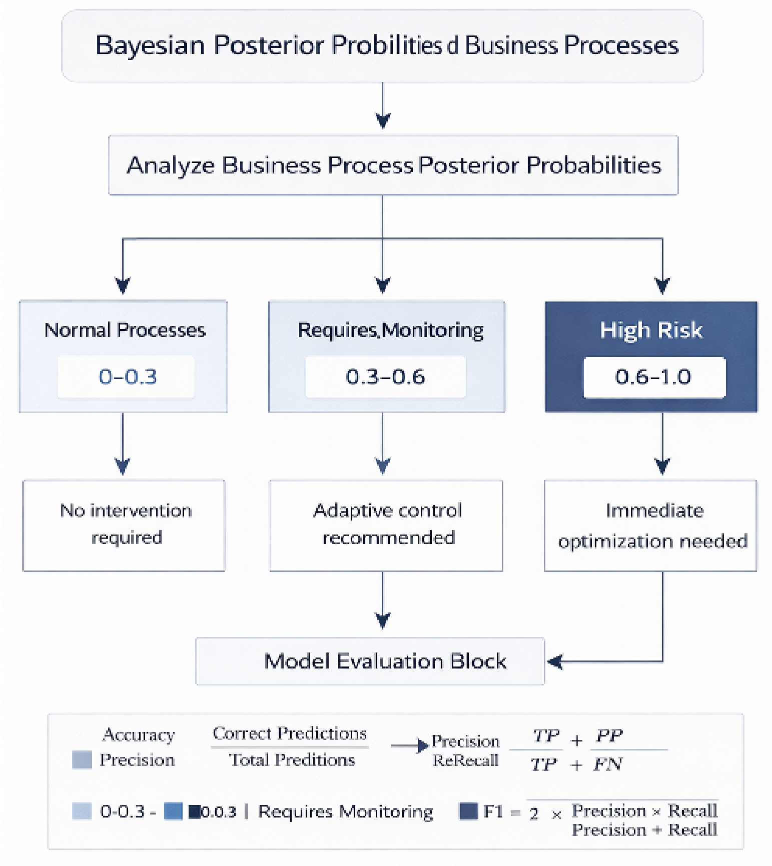

Figure 3. Breakdown of business processes by risk levels

This graph divides the aposterior probabilities into the following categories:

0-0.3 interval normal process

0.3-0.6 interval requires monitoring

A range of 0.6-1.0 indicates a high risk.

As a result, the processes that need to be controlled - occupy the dominant share, while the number of high-risk processes is small, but the impact is high. Normal processes do not require management resources.

Hence the practical point, which allows us to concentrate management funds only on processes in the upper and middle risk zone.

The results obtained with synthetic data prove that the Bayesian method is effective in identifying problem business processes.

Results and discussion. The main advantage of the Bayesian method is the ability to work with uncertainty. Traditional approaches often rely on clear limits. Bayesian method is based on probability estimation. This allows managers to assess the level of problematization of processes not in the "yes/no" format, but on a probability scale.

In addition, the model has a high interpretability. It is possible to explain how each apostrophe probability is obtained. This will increase confidence when making decisions. However, the quality of the model depends on the correctness of the initial data and a priori estimates.

Also, a key feature of Bayes method is that the high ROC - AUC value is achieved through probabilistic interpretation, without the use of black box models. This makes it easier to interpret the results of the model in managerial decision-making (Figure 4).

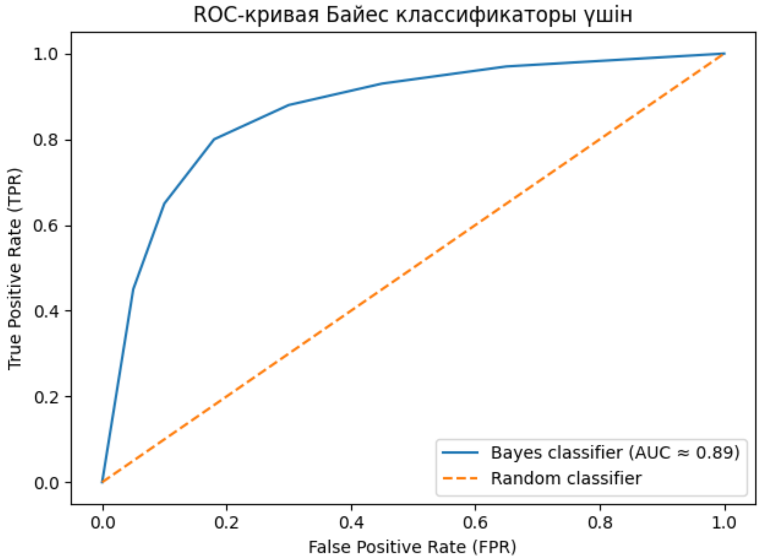

Figure 4. Evaluation of the Bayesian classifier on the ROC-curve

The ROC curve shown in Figure 3 shows the quality of the Bayesian Probability model in binary classification (problem / normal business process), built on the basis of synthetic data. Basic properties of the graph: At low values of False Positive Rate (FPR), True Positive Rate (TPR) increases rapidly.

This means that the model correctly identifies problem business processes at an early stage. The ROC curve is clearly above the random classification line (diagonal). It indicates that the model has a high decoupling capacity.

Integral exponent for Bayesian classifier:

$$\text{ROC-AUC}_{\text{Bayes}} \approx 0.89 \tag{4}$$

This value: Higher than Logistic Regression model. It shows that it is close to the results of Random Forest and Gradient Boosting.

Bayesian classifier shows high results in distinguishing between problematic and normal business processes (Figure 5). Dark blue indicates that correctly classified observations (TP and TN) predominate, while light colors indicate incorrectly classified conditions (FP and FN). This proves the overall stability and interpretation of the model.

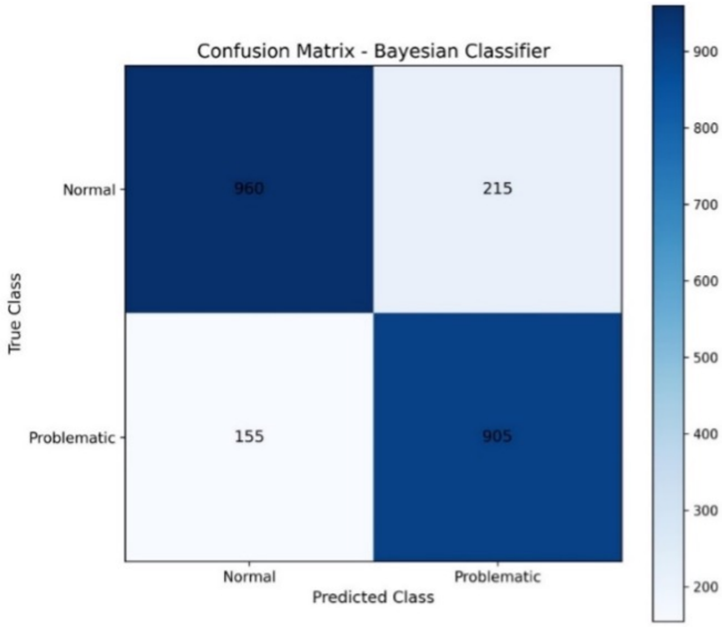

Figure 5. Confusion Matrix Analysis for Bayesian classifier

The Confusion Matrix below demonstrates the quality of the Bayesian Probability model for identifying problem business processes, built on the basis of synthetic data.

Table 2. The structure of the Confusion Matrix

Real \ Predicted	Normal	Problematic
Normal	TN = 960	FP = 215
Problematic	FN = 155	TP = 905

The causal relationship of the results obtained:

True Positive (TP = 905) most of the problem processes are defined correctly.

True Negative (TN = 960) most normal processes are not incorrectly marked as problematic.

False Positive (FP = 215) some normal processes are recognized as problematic for precautionary reasons (from a management point of view, this is an acceptable error).

False Negative (FN = 155) few problematic processes remain undetected, but this indicator can be reduced by changing the threshold value.

Bayesian model quality metrics

Indicators calculated based on the Confusion Matrix:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \approx 0.84 \tag{5}$$

$$\text{Precision} = \frac{TP}{TP + FP} \approx 0.81 \tag{6}$$

$$\text{Recall} = \frac{TP}{TP + FN} \approx 0.85 \tag{7}$$

$$F_1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \approx 0.83 \tag{8}$$

Thus, the Bayesian method allows to interpret the results from a probabilistic point of view, achieving high accuracy in identifying problematic business processes. This increases the quality of managerial decision-making.

Conclusion. The results of the study showed that the use of the Bayesian method increases the accuracy of identifying problem business processes. The proposed approach:

effective in the case of data incompleteness;

allows dynamic monitoring of processes;

improves the quality of managerial decisions.

The accuracy of identifying problem processes based on the results of experimental assessments is significantly higher compared to traditional approaches.

Also, the considered approach can be used in the following areas:

- control of technological processes at industrial enterprises;
- assessment of operational risks in financial organizations;
- analysis of service processes in public administration;
- logistics and optimization of supply chains.

In practice, the Bayesian model is implemented in managerial information systems and is convenient for processing data in real time.

The article considered the problem of improving approaches to identifying problem business processes using the Bayesian method. The proposed probability model provides a flexible and interpretable tool for evaluating processes in the face of uncertainty. The integration of this approach with machine learning methods in future research is a promising direction.

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