PLOVDIV UNIVERSITY
"PAISII HILENDARSKI"
FACULTY OF PHYSICS AND TECHNOLOGY
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Technology-based solutions for process management in telecommunications

DOCTORAL DISSERTATION SUMMARY

for the acquisition of a PhD educational and scientific degree

Field of higher education 5.Technical sciences

Professional direction 5.3 Communication and computer technology

Doctoral program: "Automation of areas of the intangible sphere (medicine, education, science, administrative activities, etc.)"

Scientific supervisor:

Prof. Nevena Mileva, PhD

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The dissertation consists of 178 pages, including text, 30 figures, 7 tables, and a list of references with 132 titles.
The numbering of the figures and tables corresponds to their presentation in the abstract.
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The public final meeting of the scientific jury will take place on March 13, 2025, at 1:00 PM in the ECIT Hall, 21 Kostaki Peev Street, at Plovdiv University "Paisii Hilendarski."

Scientific Jury:

1. Assoc. Prof. Diana Velkova Stoyanova, PhD
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3. Assoc. Prof. Eng. Borislav Hristov Milenkov, PhD
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Alternate Members:

1. Prof. Eng. Nedyalko Todorov Katrandzhiev, PhD
2. Assoc. Prof. Eng. Daniela Shekhova, PhD

The materials related to the defense are available for public access in the library of Plovdiv University "Paisii Hilendarski."

GENERAL CHARACTERISTICS OF THE DISSERTATION

Relevance of the Problem

The development of technology in recent years has brought significant changes to our reality, becoming a primary driver across all sectors of the economy. New technological solutions have created powerful tools to support management across various industries.

Accumulating knowledge and mastering new technologies have become critically important for the growth and prosperity of organizations. Working with large datasets, digitalization, the internet, cloud services, and artificial intelligence have become indispensable parts of decision-making processes.

For every organization, rapid adaptation to the changing environment through the introduction of innovative technologies, the use of new business models, and the detailed study and implementation of new modern business processes using contemporary technological solutions is now vital.

This dissertation focuses on an in-depth study and application of technological solutions to optimize the management of business processes in the telecommunications sector. The study analyzes the applicability and effectiveness of business processes in telecom companies, with a special focus on the challenges and constraints faced when implementing modern technological innovations. It highlights the competitive advantages of companies that integrate technology solutions, enabling more flexible management and process improvement.

The dissertation systematizes and analyzes in detail the existing technology-based solutions for business process management in the telecommunications sector. The leading innovations and their role in optimizing operational efficiency and increasing competitiveness are examined. Based on the research conducted, a process management system based on integrated technology solutions is designed and presented, which is designed to meet the specific needs of telecommunications companies.

The relevance of the problem related to technological solutions for process management in telecommunications is based on several key factors.

First of all, the rapid technological development of the sector and the growing number of new services, customers and requests place high demands on telecommunications companies. The increased needs and requirements of customers also create a need for innovative approaches and effective process management.

Last but not least, the sector plays a significant role in the country's economy - the share of the total volume of the public electronic communications market in the gross domestic product (GDP) of Bulgaria, calculated at current prices (source: National Statistical Institute), amounts to 2.07% (report of the Communications Regulation Commission for 2023)

Objectives of the Dissertation

The objective of this dissertation is to design and develop a technology-based system for forecasting and managing the customer retention process in telecommunications companies.

The system is designed to manage internal organizational processes related to customer service.

The system uses technological solutions based on artificial intelligence and machine learning to predict subscriber churn from a telecommunications operator. It supports management decisions related to subscriber retention and renewal of their contracts, providing precise information and analysis for effective management of the customer base.

Tasks of the Dissertation

1. Description and systematization of existing technology-based solutions for managing processes in telecommunications.
2. Investigation of machine learning models for forecasting customers who are most likely to discontinue using the operator's services by analyzing data from the information system of a telecom company.
3. Development and creation of a prototype for a technology-based system to forecast and manage the retention process of business customers in telecommunications companies.

VOLUME AND STRUCTURE OF THE DISSERTATION

The dissertation contains a title page, table of contents, introduction, an exposition presented in three chapters, conclusions and directions for future development, a declaration of originality and bibliography. The total volume of the dissertation is 178 pages.

SUMMARY OF THE DISSERTATION

Chapter 1

Description and systematization of existing technology-based solutions for process management in telecommunications

1.1. Process management in telecommunications

The beginning of the 21st century is marked by a profound transformation of business structures and the transition to an information and communication economy based on data and knowledge. In these years of digital revolution, one of the main challenges for all participants in the telecommunications sector is the rapid adaptation to the changing environment and making adequate decisions for its development, facilitating the implementation and operation of new technologies in the best way, while ensuring they are convenient and accessible to all users.

The evolution and transformation of organizational activity is a major source of achieving competitive advantage and organizations that pursue this goal must be managed through processes, operate in real time, in order to have sustainable success.

1.1.1 Business process – a tool for increasing organizational efficiency – definition and characteristics

A review of the scientific literature reveals a variety of definitions for the term "business process", the concept being popularized in the 1980s by Hammer. According to him, a process is a group of related activities that complement each other and together create additional value for customers.

A business process is described by other researchers as a group of related activities or tasks that use organizational resources, transform inputs into outputs and add value for customers. Various authors emphasize that processes include logical sequences of actions aimed at creating products or services that satisfy customer needs, while optimizing resources and supporting organizational goals.

Modern research emphasizes the characteristics of business processes as large-scale, dynamic, user-oriented and automated. They combine business and technological aspects, and their efficiency and effectiveness often depend on automation and management technologies.

The main goal of business processes is to create and deliver value for customers. This approach requires the integration of innovation, continuous improvement and effective management, which allows organizations to respond to changing market conditions. Business processes are a key element for the sustainability and success of modern companies, as they help balance technological innovation and meet customer needs.

1.1.2 Classification of business processes

The literature review shows a variety of classifications of business processes, considering different aspects of their structure and application. Michael Porter's model divides activities into primary (inputs, operations, outputs, marketing and after-sales service) and supporting (sourcing, technological development, human resource management and infrastructure), emphasizing their interrelationship for competitive advantage.
Other researchers, such as Hunt, Armistead, and Davenport, categorize processes as operational (core activities), managerial (strategic directions) and supporting (providing resources and services). In telecommunications, processes are classified as intra-organizational, ensuring efficiency within the company, and inter-organizational, related to interaction with suppliers and partners.

1.1.3 Classification of business processes in telecommunications

The effective management of business processes, both intra-organizational and inter-organizational, is a critical factor for the success of telecommunications companies. These processes play a key role in the adaptation to the dynamic environment and the sustainability of organizations, transforming internal resources into information services that meet market needs. The analysis of business processes in the sector distinguishes two main groups: strategic processes related to the development of infrastructure and products, and network operations focused on customer support and service.
Classification models, such as that of APQC, structure processes into two categories: operational (aimed at providing services and managing customers) and management and support processes (ensuring coordination and resources for effective functioning).
In addition, another important classification of processes in the telecommunications sector is provided by the eTOM framework, widely accepted in the telecommunications industry. It divides processes into three vertical functional groups: Group 1 - strategy, infrastructure and product, Group 2 - operations and Group 3 - management. In addition to the vertical structure, the eTOM framework also decomposes processes into horizontal blocks, providing a structure for standardization and effective management. The horizontal blocks include four main areas:
Market, product and customer processes - cover marketing activities, new product development and customer relationship management.
Service processes – related to the provision and maintenance of services to customers.
Resource processes – management of networks, systems and other resources required for operations.
Supplier processes – cover interactions with partners and suppliers providing services or resources.

1.1.4 Integrated classification of business processes in telecommunications companies: An approach to optimization, management and coordination

Taking into account the various classifications of business processes, as well as the development guidelines of telecommunications operators, we propose a new classification, which is summarized and presented in Table 1.

In the proposed classification, we have considered the rapid development of telecommunications, the expanding range of services and equipment, and the growing interaction with other companies, which necessitate more careful and in-depth establishment and coordination of stable inter-organizational processes to ensure consistency and superiority of the services offered.

Classification/ Categorisation	Process Type
Scope	Intra-organizational
	Inter-organizational
Process area	Strategic
	Management
	Operational
Functionality	Market, product and customer processes
	Service management and development processes
	Resource processes
	Processes with partners and suppliers
Complexity	Simple
	Hybrid
	Technological

Table 1. *Classification of business processes in telecommunications companies*

The proposed classification of business processes in telecommunications companies combines four main criteria: scope, area, functionality and complexity. The processes are divided into internal, which are carried out entirely within the company, and inter-organizational, requiring interaction with partners and suppliers. By area, they include strategic processes for long-term planning, managerial for current operations and operational for daily activities.

The classification by functionality focuses on marketing, service management, resource support and interaction with suppliers. By complexity, the processes range from simple routine tasks to complex technological operations that require coordination and specialized skills.

This classification provides a clear framework for management, optimization and competitive advantage in the dynamic telecommunications sector.

1.2. Technological solutions in process management in telecommunications

Over the past two decades, the intensive development of information technologies and digitalization has faced telecommunications companies with the need for a radical transformation of business processes. These changes, linked to the new conditions of the digital economy, require the integration of modern technologies such as the Internet of Things (IoT), artificial intelligence (AI) and big data analysis (Big Data). Technologies play a key role in automation and intelligent process management, transforming traditional models into adaptive and connected systems.

Modern trends in business process management emphasize the importance of automation, personalization and adaptability in an unstable and dynamic economic environment. In this context, the telecommunications industry is positioned as one of the most affected from the digital transformation, where modern technologies and intelligent solutions play a central role in creating sustainable and efficient organizational models.

1.2.1 Technological solutions in process management in telecommunications when integrating the Internet of Things (IoT) technology

The Internet of Things (IoT) is a global network of connected devices and systems that interact, collect and analyze data in real time. This technology transforms businesses by enabling automation, predictive maintenance and intelligent resource management. In telecommunications, IoT optimizes networks, improves customer service and opens up opportunities for new services such as smart homes and smart cities.

By 2030, according to Statista, IoT is expected to connect over 32 billion devices, creating significant opportunities for telecommunications companies and driving innovation in the global economy. Participation of IoT technology in processes of different functional groups in the telecommunications company:

Marketing and customer service – IoT transforms customer interaction through:

Personalized marketing: Data collected by IoT devices allows for analysis of customer behavior and creation of targeted promotions and offers. On-demand pricing: IoT collects real-time data that allows for dynamic adaptation of prices according to market demand and individual customer needs.

Customer experience management: IoT devices allow for rapid detection and response to problems, improving service quality and customer satisfaction

Service management and development processes – IoT provides opportunities for telecommunications operators to develop new business models for managing their services and thus increase their revenues and profits.

Resource processes – IoT in the telecommunications industry provides a number of opportunities for improving and optimizing network management: equipment monitoring, proactive maintenance management, network resource optimization, network security management, energy efficiency management, people management.

1.2.2 Technological solutions in telecommunications process management when integrating cloud technologies

Cloud technologies are defined as a model that provides access to shared computing resources (networks, servers, applications, etc.) on demand, with minimal management efforts. They allow for the expansion or reduction of resources according to user needs and offer a cost-effective solution for processing large volumes of data and improving efficiency.

In the telecommunications industry, cloud computing is key both for operational efficiency and for entering new business areas. It transforms traditional business models, moving from product-based to service-based structures, which improves delivery time, flexibility and reduces costs.

Processes related to marketing and customer service

Cloud technologies transform customer interaction by providing:

Improved data management and service personalization: Cloud platforms provide tools for analyzing and processing customer data, improving customer satisfaction and experience.

Data security: Provide protection through encryption, access control, and reliable storage.

Mobility and accessibility: Provide the ability to manage customer services from any device connected to the Internet.

Disaster recovery: Ensure rapid data recovery and service continuity.

Reduced operating costs: By eliminating the need for physical infrastructure and simplifying processes.

Marketing strategies: Cloud platforms facilitate the development of personalized promotions and campaigns based on customer behavior.

Processes related to service development and management

Cloud technologies provide opportunities for the development and delivery of new services through different business models:

SaaS (Software as a Service), PaaS (Platform as a Service), IaaS (Infrastructure as a Service), CaaS (Communication as a Service), EaaS (Everything as a Service): Consolidates multiple cloud services into a single platform, enabling a complete solution for the business.

Resource processes: Development and management of resources (network, computers, applications)

Cloud technologies improve the management of network and resource processes through:

Network resource management: Virtualization and automation simplify the management and scaling of network infrastructure.

Integration with 5G and Edge Computing: Combining cloud technologies with 5G provides high speed and low latency, optimizing data processing.

Energy optimization: Intelligent systems reduce energy costs and improve the efficiency of network operations.

Monitoring and Maintenance: Enable real-time monitoring and predictive maintenance of equipment.

1.2.3 Technology solutions in telecommunications process management when integrating Big Data Analytics (BDA)

The telecommunications industry processes huge volumes of data daily, generated by smartphones, social media, IoT devices and next-generation networks. According to the Ericsson Mobility Report, the volume of data is expected to grow by over 60% by 2025. This data is diverse, including information about calls, internet sessions, geolocation and network performance, and can be processed in real time or in batches.

Marketing and customer service processes

Using customer data: Big data analytics provides detailed customer profiles by processing information from social media, internet activity and historical behavioral data.

Personalization: BDA enables personalized promotions and commercial offers that improve the customer experience. Prediction of customer problems and offering solutions before they occur increase satisfaction and loyalty.

Revenue growth: Data analytics enables partnerships with advertisers and other businesses to create new revenue streams.

Service development and management processes

Fraud detection: BDA is used to detect SIM boxes, reducing revenue loss and improving network performance. New service creation: By analyzing customer transaction data, operators can offer personalized coupons and promotions, driving sales.

Innovative business models: Data analytics helps create new offerings for business customers, improving their efficiency.

Resource processes: Network, computing, and application management

Network optimization: Big Data helps optimize 4G and 5G networks through end-to-end visibility, self-coordination, and proactive tuning of network performance.

Supplier Processes

Real-time delivery tracking: BDA enables monitoring of the movement of goods and components, which improves delivery accuracy and reduces downtime. By collecting and analyzing data on delivery times, quality of delivered goods, and compliance with agreements, companies can evaluate the performance of their suppliers and improve planning. Data analysis on price trends and market conditions helps make better decisions when negotiating terms. BDA helps identify potential supply problems, such as geopolitical risks, natural disasters, or financial instability of suppliers.

1.2.4 Technological solutions in telecommunications process management when integrating Artificial Intelligence

The term "artificial intelligence" (AI) was first introduced by John McCarthy in 1959 - AI is defined as the science of creating intelligent machines and computer programs that imitate human intelligence.

Basic Techniques in Artificial Intelligence:

Expert systems (ES); Natural language understanding (NLU); Machine learning (ML); Neural networks (NN) and genetic algorithms (GA); Distributed artificial intelligence (DAI); Robotics.

Processes related to marketing and customer service

Virtual agents and chatbots - AI-based chatbots and conversational agents play a key role in customer service automation. They use natural language processing (NLP) and machine learning technologies to communicate with customers, answer queries, and solve problems.

In Bulgaria, company A1Bulgaria EAD uses the AVA chatbot, developed with the Teneo platform. AVA offers personalized assistance for managing services, payments and roaming.

Automated Customer Care (ACCR) systems apply machine learning to analyze network metrics and customer records to identify the causes of problems. This leads to resource optimization and reduced operational costs.

AI helps identify customers at high risk of churn, allowing operators to take proactive measures such as personalized offers and improved services.

AI optimizes sales processes through the following approaches:

Lead Generation: By analyzing text, voice, and visual data, AI identifies potential buyers and creates targeted lead lists.

Personalized Communications: AI uses behavioral data to deliver targeted advertisements and personalized offers, enhancing customer engagement.

Product Recommendations: AI analyzes past purchases to suggest additional products, increasing cross-selling and upselling opportunities.

Machine learning algorithms determine the most appropriate prices based on customer data and market conditions. AI significantly improves efficiency and results in marketing and customer service, while creating better experiences and generating added value.

Service development and management processes

Artificial intelligence (AI) plays a key role in developing new services and improving existing ones. AI optimizes fraud detection and improves cybersecurity by analyzing network data and automating decisions. AI-powered virtual digital assistants extract key information from emails and web forms, providing automated responses and query processing. AI enables the creation of differentiated services, such as intelligent security solutions, automation and data analytics, that improve customer experience and operator efficiency.

Examples of AI-powered solutions in Bulgaria include: Chatbot SaaS, A1 Cyber Backup, A1 Video Security, intelligent video surveillance from Vivacom.

Resource processes: network, computing and application management

AI supports traffic forecasting and optimal resource allocation through neural networks, swarm intelligence and genetic algorithms for energy-efficient routing.

Bayesian filtering and machine learning optimize optical transmission parameters such as amplitude and phase noise.

Software-defined networks (SDN) provide automated self-healing through dynamic configuration and restart of servers without human intervention.

AI identifies network problems, detects revenue leakage and fraud in billing and roaming. Infrastructure as a Service (IaaS) enables virtualized infrastructure, facilitating resource sharing and optimization among operators. Robots automate routine tasks such as data entry and processing, while AI optimizes staff selection through data analysis and predictive performance assessments.

Supplier Processes

The use of artificial intelligence (AI)-based technology solutions plays a key role in improving and managing supplier processes. These solutions offer innovative optimization and automation tools that transform traditional supply chain approaches.

AI technologies achieve significant improvements in all stages of the purchasing process – from identifying needs, negotiating and concluding contracts to delivering products or services. AI automates contract management by monitoring framework agreements, identifying renewal opportunities and suggesting real-time adaptations based on business needs.

An important aspect of these technology solutions is the analysis of key performance indicators (KPIs), quality control and reduction of discrepancies. AI uses predictive analytics to process large volumes of data, detecting problems that are not obvious during manual analysis, and provides proactive recommendations for action.

AI technologies also facilitate the processing of documents, including handwritten ones, by extracting and adapting relevant information according to the specific requirements of buyers. This speeds up processes, ensures greater accuracy and increases the efficiency of interaction with suppliers.

Summary:

Advanced technological solutions play a transformative role in managing processes in telecommunications. The implementation of new technologies such as the Internet of Things (IoT) allows for automation and connectivity of devices, which optimizes processes. Cloud technologies provide flexibility and facilitate access to data, while big data analytics helps companies analyze large volumes of information for better decisions and personalization of services. The integration of artificial intelligence supports automation and provides intelligent solutions to improve customer service. The implementation of AI in analysis and forecasting processes not only improves the efficiency and reliability of systems, but also leads to significant economic benefits, such as cost reduction and resource optimization. This highlights how the use of AI not only improves operational efficiency, but also contributes to the long-term sustainability and financial stability of organizations.

Therefore, we consider it well-founded to develop a system utilizing technology-based solutions for process management within the telecommunications industry. The focus will be on processes related to marketing and customer service, with a particular emphasis on the integration of artificial intelligence. These processes have been selected due to their critical role in ensuring customer satisfaction and enhancing the competitive positioning of companies. The integration of AI represents a logical progression toward improving service quality and enabling the personalization of the customer experience.

Chapter 2

Development of a Technology-Based System for Managing the Retention Process of Business Customers in Telecommunications

2.1 Customer churn as a global business problem

The term “churn” was introduced by Berson et al., and is a key concept in customer flow management in the telecommunications sector. According to the authors, “churn” is defined as the process by which customers leave or terminate the services of a given operator. This concept is key to understanding the dynamics of the customer base and to developing strategies for customer retention, reducing customer churn and optimizing marketing and service strategies. Effective customer management includes the ability to predict the likelihood of customers changing service providers, measure their profitability and implement strategic and tactical measures to retain customers and reduce churn.

The main source of revenue for telecommunications companies is monthly subscription fees and services used, which makes retaining existing customers a strategic priority. Since attracting new customers is approximately five times more expensive than retaining current ones, effective strategies to reduce churn are essential for long-term profitability.

The telecommunications industry is extremely competitive, but despite efforts to build loyalty, it faces a high rate of customer churn (15-45% according to "Harvard Business Review"). Data from "Aspect" further confirms the high churn rate in the sector - an average of 20%. This highlights the critical need to focus on customer retention to improve the sustainability and competitiveness of operators.

The telecommunications market in Bulgaria is dominated by three companies: Vivacom Bulgaria EAD, A1 Bulgaria EAD, and Yettel Bulgaria EAD. Together, they hold 100% of the mobile market and 97.8% of the fixed telephony market. They operate in an oligopolistic market with an almost even distribution of shares. In 2023, the mobile market shares by subscribers were: A1 – 36.2%, Jettel – 31.4%, Vivacom – 32.4%. By revenue, the shares were: Jettel – 40.7%, A1 – 29.9%, Vivacom – 29.4%.

The penetration of mobile services reaches 124.3% of the population with 8.01 million subscribers by the end of 2023, which highlights the high saturation and limited opportunities to attract new customers. In this competitive environment, market share growth is achieved primarily by attracting subscribers from competitors.

The number portability procedure introduced in 2008 allowed consumers to change their provider while keeping their phone number. This facilitated and strengthened the competitive environment, removing one of the main barriers for the customer – the need to change their phone number. The data shows that by the end of 2022, 2.96 million mobile numbers were ported, which significantly affects the dynamics of the market. In the last four years alone (2019–2022), the number of ported numbers has increased by 26.9% to 250,399 – Figure 1 shows the ported numbers in Bulgaria for the period 2019-2022.

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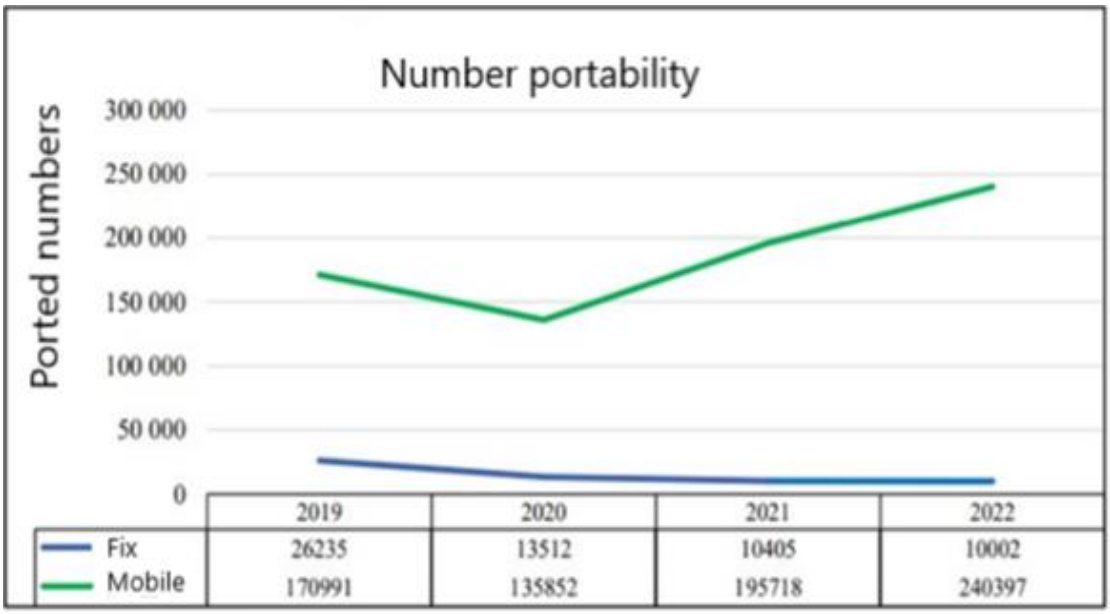

Figire 1. *Ported numbers Bulgaria 2019-2022, Source Communications Regulatory Commission*

This trend indicates increasing customer mobility, as Bulgaria is gradually approaching the average European levels of portability.

2.2 Customer retention in the telecommunications sector: strategies and challenges

In the study, the term "retention" is used to refer to strategies for customer retention and loyalty management, which is a top priority for telecommunications companies. The process includes proactive actions to prevent customer churn through personalized solutions and building barriers against switching. The main goal is to extend the customer life cycle and and increase the customer's overall value to the company.

The customer life cycle encompasses stages such as acquisition, development, proactive and reactive contract renewal, as well as possible reactivation after churn. Extending this cycle requires not only retaining valuable customers, but also managing unprofitable ones to minimize possible negative effects on other customers. Key retention factors include service quality, personalization, pricing, innovation, and satisfaction, with high satisfaction typically strengthening customer relationships.

Barriers to change also play an important role, but they must be built as positive advantages that competitors will find difficult to overcome. Effective retention requires predicting the risk of churn through customer behavior analysis and implementing targeted actions to reduce this risk. Reliable forecasting models enable companies to identify at-risk customers and implement targeted measures to retain them. These efforts are crucial for achieving sustainability and profitability in the face of strong competition.

2.3 Analysis of the Retention Process for Business Customers in Telecommunications Companies in Bulgaria

The retention process is a key element in customer relationship management in telecommunications companies. It covers building customer loyalty, predicting churn and implementing targeted retention strategies through defensive sales approaches.
When analyzing the retention process in the telecommunications sector, it is necessary to take into account the differences between the retail and business customer markets. Each of these markets requires different organizational approach and service methods, and the processes related to customer relationship management are specific to the respective segment.
The dissertation focuses on the business customer market, providing a detailed analysis of the retention process. As part of the study, interviews were conducted with 16 key participants in the process, including operational and account managers, as well as employees from analysis departments. In addition, direct observation of retention activities was carried out.
Based on the collected data, a model of the Business Customer Retention process was developed, which systematizes the main stages and strategies supporting the successful retention and management of relationships with this specific customer segment.

2.3.1 Model of the Retention Process for Business Customers

The Retention process for business customers in Bulgarian telecom operators was modeled with Enterprise Architect v.17 software.
Enterprise Architect, developed by Sparx Systems, is a widely used modeling tool designed for various industries and applications, including software engineering, systems modeling, business processes, and solution architecture. The model of the retention process for business customers is presented in Figure 2.

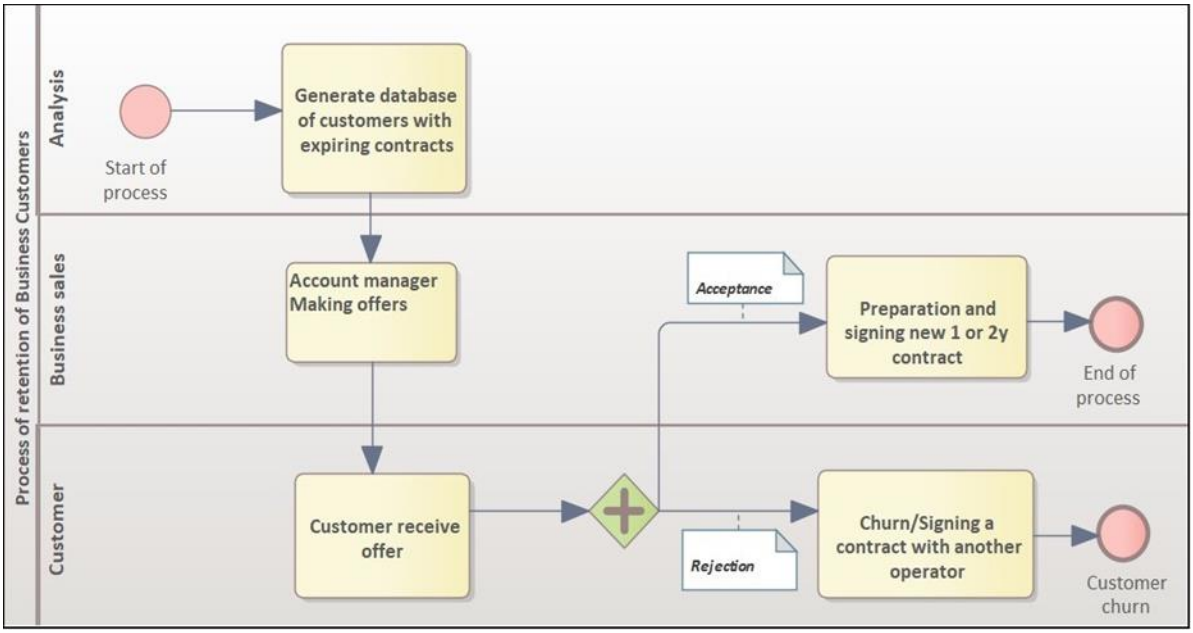

Figure 2. *Model of the Retention Business Process for Business Customers (authored, created using the Enterprise Architect software tool)*

1.Start of the process. The process begins with an analysis aimed at identifying customers with expiring contracts.
2.Generation of a database of customers with expiring contracts. A database is created containing customers whose contracts are about to expire, enabling measures to be taken for their retention.
3.Creation of offers by the account manager. The account manager prepares individual offers for customers in order to retain them as customers and sign contracts with them for a new term of 1 or 2 years.
4.The customer receives an offer.
5.Customer decision:
• Acceptance of the offer – If the customer accepts the offer, a new contract for 1 or 2 years is prepared and signed.
• Rejection of the offer – If the customer rejects the offer, the contract is terminated and the customer signs with another operator.
6.End of the process. The process ends in two possible scenarios:
• Successful retention of the customer by signing a new contract.
• Churn, when the customer decides to sign a contract with another operator.
Participants in the process are:
1. Business Analysis Department, which generates from the software products used by the telecom, the customer base for re-signing
2. Business Sales Department - account manager, directly responsible for the process
3. Business customers.

2.3.2 Analysis of the Retention Process for Business Customers

The study analyzed the Business Customer Retention process in Bulgarian telecommunications companies, using the Business Process Analysis methodology - BPM CBOK. The analysis covers the business context, organizational culture, performance indicators, customer interactions, bottlenecks, variations, costs and process control. Data from interviews and observations were used.

Business context: The process is key to retaining the customer base and corresponds to the strategic goals of the operators. Its main focus is to guarantee the use of services through subscription contracts, which limit the switching of customers to competing operators. External risks include increased competition, economic challenges and predatory pricing, while internal risks are related to delayed bidding and insufficient control.

Organizational culture: The process is led by operational-level managers and includes incentive bonus schemes tied to indicators such as the percentage of re-signed contracts and lost customers This ensures commitment and a focus on efficiency.

Efficiency: The process efficiency ranges between 60-80%, with churn rates fluctuating.

Customers and interactions: Customers are segmented into small, medium and large companies based on the number of subscribers and the values of their monthly invoices. Their main

expectations include competitive prices, promotional offers, enhanced service and upgraded devices. Customers interact with the process primarily occurs at the time of contracts expiration.

Bottlenecks and Variations: The main bottleneck is the bidding stage, which often depends on the subjective judgment of account managers. This results to variations in the order and efficiency of the process, especially for customers from small and medium-sized business segments.

Costs and Control: Costs include subsidized devices and operational activities, but must be combined with optimization to increase returns. Process control is provided through metrics such as number of re-signed contracts, lost customers, and value of lost revenue.

The Retention process is a key tool for minimizing churn and maximizing customer value, while ensuring long-term profitability and competitive advantages for telecommunications companies.

2.3.3 SWOT analysis of the Retention Process for Business Customers

The Retention Process for Business Customers was analyzed using a SWOT analysis, which reveals key internal and external factors affecting its performance and effectiveness.

Strengths:

1. Clearly defined roles in the process
2. Committed organizational leaders involved in the process
3. Clear and specific indicators of the effectiveness of the process
4. Incentives designed to improve process outcomes
5. The process has well-established control over the final result.

Weaknesses:

1. The process includes a stage that is influenced by personal judgment
2. There are many variations in the order and timing of bidding
3. Bidding delays can reduce the time available for process implementation
4. Frequent exceptions to the rules during client negotiations
5. Lack of predictability of the process
6. Operations managers have limited ability to plan necessary resources for the process

Opportunities

1. Development of technology-based solutions for process management
2. Advancements in artificial intelligence and machine learning technologies
3. Improvements in customer churn prediction techniques

Threats

1. Strong competition in the market
2. Economic risks, including inflation or reduced consumer spending power
3. Regulatory changes related to contractual relationships.
4. Regulatory changes related to increasing the possibility of new market participants entering the market.

All of the threats described require adaptability and strategic proactivity on the part of companies, which must develop more flexible solutions and personalized offers in order to maintain their competitiveness and retain their customers in a dynamic market environment. By understanding

these factors, an organization can develop better strategies to optimize the Retention process and increase the loyalty of its business customers.

2.3.4. Proposal for a redesign of the Retention Process for Business Customers

The redesign of the Business Customer Retention process is a systematic improvement aimed at increasing efficiency, optimizing costs and enhance customer satisfaction through the integration of innovation and technology.

Based on the SWOT analysis, significant optimization potential was identified through an artificial intelligence solution for predicting customer churn. The AI prediction system will help prioritize customers with a high risk of churn, improve the allocation of time and resources, and provide additional opportunities for customer retention – figure 3.

Process steps:

1. A database is generated containing all customers in a given region whose long-term contracts expire within the next three months, as well as those with expired contracts.
2. The operations manager uses a churn prediction system to prepare a time schedule and determine performance indicators.
3. An account manager prepares offers for re-signing customers with expiring contracts based on the schedule and presents them to the customers.
4. The customer receives and reviews the offer and decides whether to accept or reject it.
6. If the offer is accepted, a contract is prepared and signed, successfully concluding the process.
7a. If the client does not accept the offer, the process ends with the client's churn.
7b. If the client does not accept the offer, an additional option is possible - preparing a second offer and re-offering to the client.

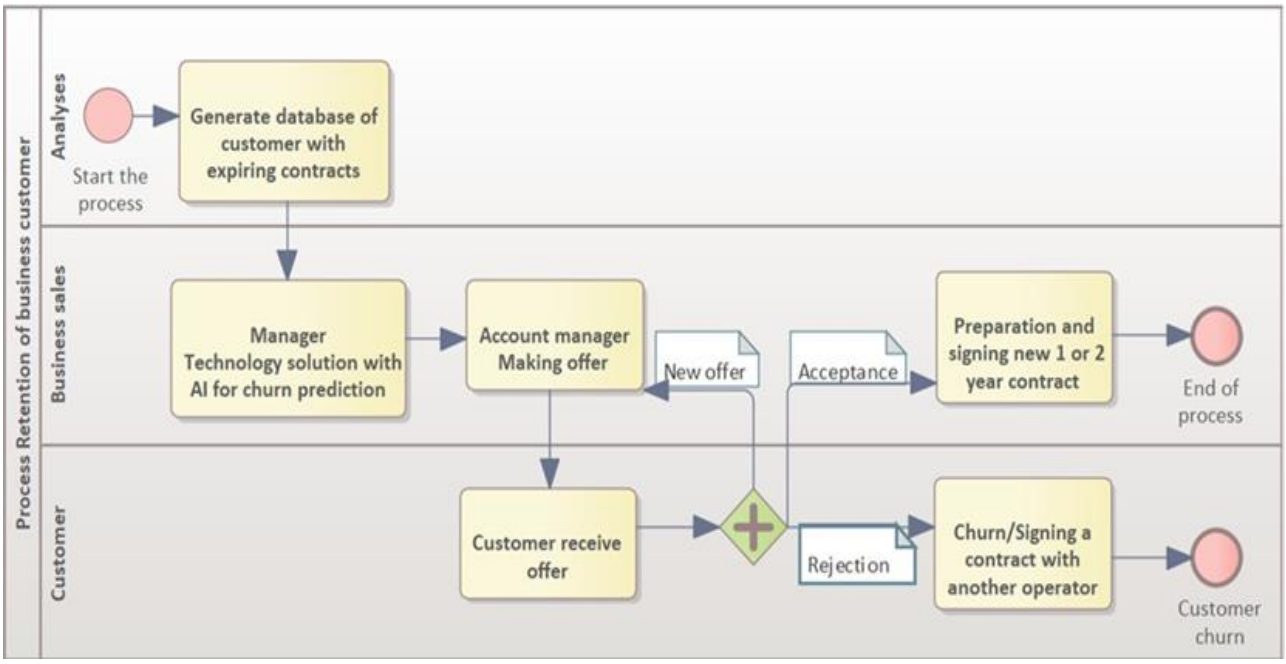

Figure 3. *Model of the Retention Business Process for Business Customers To-be (authored, created using the Enterprise Architect software tool)*

The benefits of process redesign are:
Improved planning: The forecasting system will assist operational managers in cost analysis and resource planning.
Prioritization of efforts: Customers with high churn risk will receive attention at an early stage, which will improve retention likelihood.
Reduction of variations: Automation and standardized procedures will minimize subjective judgment and delays.
Increased efficiency: Additional metrics and motivating factors for account managers will improve their engagement and results. Redesigning the Business Customer Retention process through AI integration will lead to significant improvements in process efficiency.

2.4. Design and development of a business customer churn prediction system

This section presents a churn prediction system that we will implement as a technological solution in the Business Customer Retention process in telecommunications companies.
The goals for developing this system are:
• The system should be reliable: the results of the forecast should be reliable and practically usable.
• To use data that every operational manager has access to and not require additional activities to collect data related to customer satisfaction, customer complaints, etc., which would lead to extra costs.
• The system should be practical and easy to use.
The forecast will focus on customers voluntarily leaving to switch to a competing operator. This excludes forced refusals (e.g. due to unpaid debts or fraud), which are management decisions of the operator.

System design and development stages

The development process consists of the four main stages described in the literature, with an additional stage added for data preprocessing to ensure the quality of the input data – Figure 4.

1. Data identification and collection

Collection of key information about customers, including payment history, contract duration, frequency of service use and other significant indicators necessary for the forecast.

2. Data preprocessing

Transformation, cleaning and normalization of data before analysis.

3. Data Splitting

Splitting the data into training and test datasets.

4. Training a predictive model

Training the model using machine learning techniques.

5. Validation of results

Validation ensures that the system provides reliable results corresponding to actual churn.

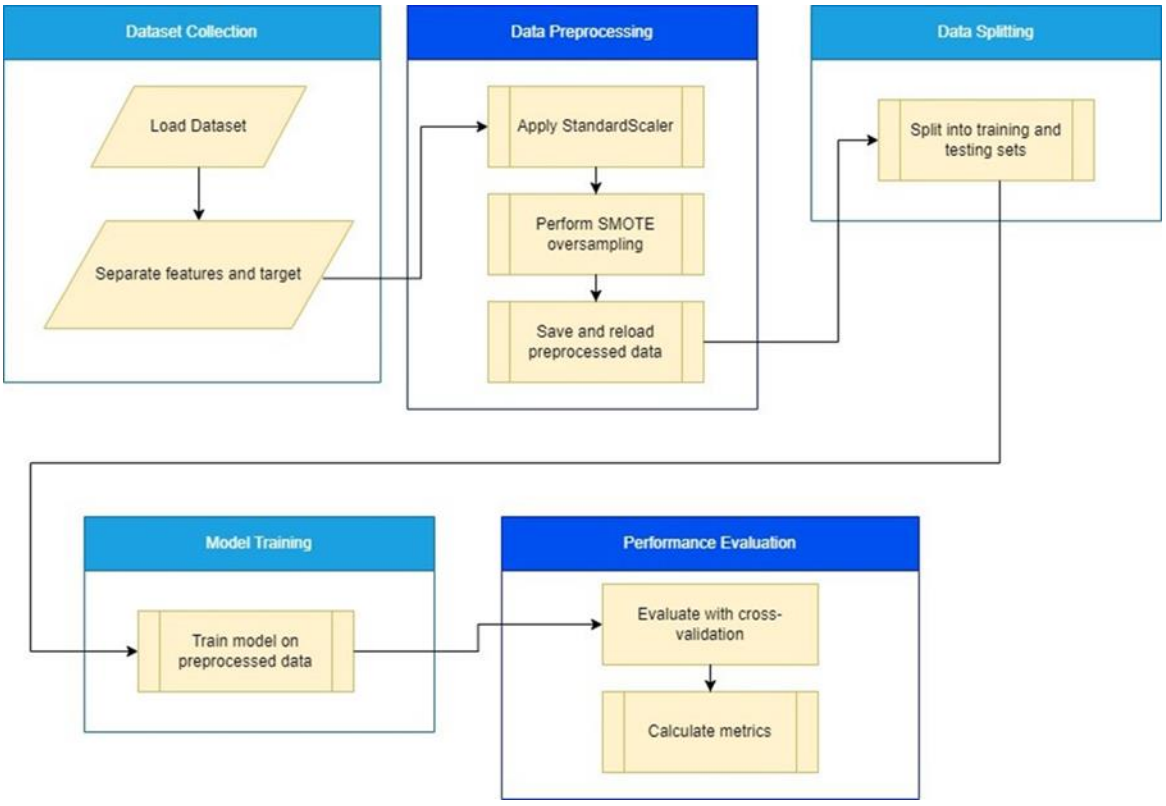

Figure 4. *Stages of design and development of a system for predicting churn of business customers*

By integrating forecasting technologies, the system will improve the efficiency of the process and provide a strategic advantage in the dynamic telecommunications industry. We will sequentially consider each stage and identify possible challenges.

Stage 1: Data Collection

The quality of the data is critical for the accuracy and reliability of a business customer retention forecasting system. The selection of appropriate data that reflects the characteristics and behavior of customers determines the effectiveness of the model. Due to the high costs and limitations of collecting specific information, such as customer satisfaction data, the system will use available operational data routinely utilized in telecommunications companies.

An important clarification when developing the system is that the data is real and is used in the daily work of an operational manager in a mobile operator in Bulgaria. They are not pre-selected and selected, since our goal in developing the system is its practical applicability and real management of the Business Customer Retention process in telecommunications. After loading the data, the next important step is separating the features from the target variable.

The features in our database are:

CRM Value Segment

Effective Segment

Billing Zip Code

CA Name

Number of active subscribers
Number of inactive subscribers
Number of terminated subscribers
Total number of subscribers
Avg. mobile revenue
Avg. FIX revenue
Total revenue
ARPU – average revenue per subscriber (SIM card)

Out of 8453 customer records, 7% of them are churned (i.e. left the provider). This creates a significant imbalance in the data, and with such a small percentage of churned customers, the database becomes extremely unbalanced. The target variable in the dataset is defined as binary: 'Yes/No,' where 'Yes' indicates that the customer has left the operator, and 'No' indicates that the customer has stayed.

This disparity between classes is one of the main problems faced by the customer churn prediction model. Such an imbalance can lead to a predominance of "No" classifications, as the model would learn to predict the dominant class, ignoring the minority class with customers who have left. This can lead to significant forecast errors, as the system will not correctly account for true churn cases. Furthermore, the dataset contains noise and missing values, which further complicates the process of building a predictive model. Missing values can result from incomplete or corrupted records, while noise in the data can arise from incorrect or atypical customer behavior, which can cloud the forecast results. To ensure high-quality forecasting, it is necessary to resolve these issues through data preprocessing techniques.

2.4.2 Stage 2: Data preprocessing

Data preprocessing is a critical step in building predictive models, as it ensures accuracy and efficiency. This process transforms raw data into a suitable format for machine learning by normalizing, balancing classes, and handling missing values.

Data Scaling (StandardScaler):

To avoid dominant features with different scales, we used the StandardScaler method, which standardizes feature values by removing the mean and scaling by the standard deviation. This is important for models such as logistic regression and SVM, which are sensitive to the magnitude of the input data.

SMOTE (Synthetic Minority Over-sampling Technique):

SMOTE was applied to balance the classes in the dataset by increasing the number of minority classes (churn) using synthetically generated samples. This technique uses linear interpolation between existing samples and their nearest neighbors, thus avoiding duplication and creating new, distinct records.

Results of Data Preprocessing:

The initial data imbalance (7% churn) was corrected by adding 7353 new synthetic records, which increased the data set from 8453 to 15806 records. This balanced structure improved the accuracy of the model, allowing for better representation of the minority class.
By combining scaling and SMOTE, we significantly improved the quality of the data, providing a better basis for building an accurate and efficient churn prediction model.

2.4.3 Step 3: Splitting the Dataset

Separating the data into training and testing subsets is an essential step in building a reliable churn prediction system.
Training subset: This part (80% of the data) is used to train the model, allowing it to analyze and recognize patterns in the data. We used 12644 records for training.
Test subset: The remaining 20% of the data (3162 records) is used to evaluate the performance of the model. By testing on unknown data, we verified the model's ability to predict churn.
This approach ensures an objective assessment of the accuracy and generalizability of the predictive model, providing the basis for a reliable forecasting system.

2.4.4 Stage 4: Development of a predictive model

Customer churn prediction requires a variety of methods and algorithms that can identify patterns and characteristics leading to customer churn. The following main models were used in this study:
Logistic Regression
Decision Trees
Support Vector Machines (SVM)
Naive Bayesian Algorithm
Random Forest
Adaptive Boosting (AdaBoost)
Extra Trees Classifier
Linear Discriminant Analysis (LDA)
All the listed models were applied in the development of the churn prediction system, and their final performance was analyzed using a test subset of the data.

2.4.5 Stage 5: Validation of the results

Validation of the results is a key stage in the development of the business customer churn prediction system. It ensures the reliability and accuracy of the forecasts, as well as the applicability of the model in real conditions. The main validation and evaluation methods include:
Validation method

1. Cross-validation

Model evaluation metrics

1. Accuracy: Measures the overall correctness of the model against all observations:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

It is appropriate for balanced data, but may be misleading when there is imbalance between classes.

2. Sensitivity (Recall/Sensitivity): Evaluates the model's ability to correctly identify all positive cases:

$$Sensitivity = \frac{TP}{TP + FN}$$

3. Precision: Measures the accuracy of positive predictions

$$Precision = \frac{TP}{FP + TP}$$

4. F1-score: Balances precision and sensitivity:

F1-Score = (Precision ∗ Recall ∗ 2)/(Precision + Recall)

5. ROC-AUC (Receiver Operating Characteristic – Area Under Curve) – Measures the ability of the model to distinguish between positive and negative classes for different classification thresholds. A value of 0.5 indicates a random guess, and a value of 1.0 indicates perfect classification.

A combination of various validation methods and evaluation metrics provides a comprehensive overview of the predictive model's performance. Selected metrics such as ROC-AUC and F1-score are critical for reliable evaluation, especially in the case of imbalanced classes typical of churn analysis. These approaches ensure that the model is both applicable and effective in real-world business scenarios.

2.5. Prototype of a Business Customer churn prediction system

The business customer churn prediction system is available through the Hugging Face Hub platform – an online service for hosting and sharing projects in the field of artificial intelligence and machine learning. It is available at:

https://huggingface.co/spaces/hhhar/ChurnPredUpdated.

Hugging Face Hub offers Git-based repositories for models, data and web applications, which facilitates collaboration, version control and demonstration of AI applications. The platform can host models used for natural language processing, computer vision and audio tasks, such as text classification, object recognition and automatic speech recognition. This makes the system easy to integrate and test by developers and users.

2.5.1. Methodology of the Business Customer churn prediction system

The methodology for predicting business customer churn in the telecommunications sector follows the stages described in section 2.4.

The models are evaluated using validation approaches such as accuracy, sensitivity, precision, F1-score and ROC AUC to identify the most effective churn prediction model.

2.5.2 Interface Description

The interface of the customer churn prediction system was developed using the Streamlit SDK (https://streamlit.io). The key components of the interface include modules for data entry,

visualization of results, and presentation of predictions in a clear and understandable form. The selected models were selected based on their effectiveness in predicting drafts.
The entire view of the application with all its components is presented in Figure 5.

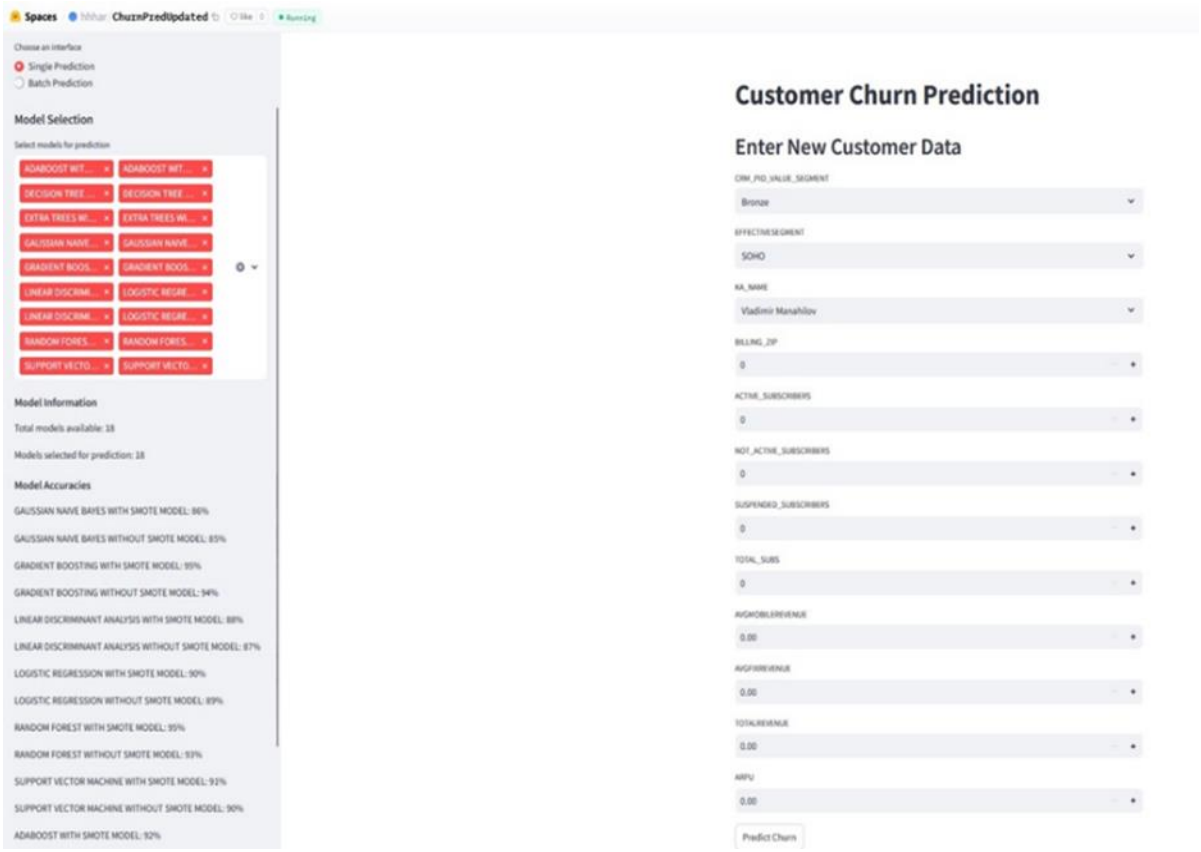

Figure 5*. General view of the application of the business customer churn prediction system*

The application is organized into two main sections:
• Model Selection and Information (sidebar):
Users can choose from multiple machine learning models for prediction.
• Main Content Area:
Contains input fields where users can enter specific customer data.
The "Churn Prediction" button triggers the prediction process and the results are displayed in terms of:

- Individual model predictions,
- Overall prediction based on weighted voting,
- Probabilities of churn,
- Graphical visualization of the predictions.

The customer churn prediction system also offers so-called "batch prediction".
When the Batch Prediction button in the sidebar is selected, the system allows loading a csv file with a dataset generated by a telecom operator's information system of customers with expiring contracts subject to renegotiation.

After uploading the file, the system processes it through all trained models with and without SMOTE and generates individual csv files with marked potential churn customers. In this way, the operations manager can efficiently allocate these business customers to account managers for urgent negotiations, preparation of offers and renegotiation of contracts, in order to prevent companies from switching to another telecom operator.

Functionalities

Multi-model forecasting: Users can choose from different churn prediction models, increasing robustness by combining their capabilities.

Weighted voting system: The system uses the model accuracy to weight the predictions, creating a more reliable overall forecast.

Interactive customer data entry.

Visual and text output: The prediction results are displayed both as text outputs (probability of leakage, probability of dropout) and as graphical representations (bar chart), offering clear and interpretable results.

Flexibility: The application is compatible with both full pipeline models and standalone classifiers, providing flexibility in choosing a model according to different data types or specific prediction tasks, depending on the user requirements.

2.6 Technologies used and key components

In the development of the churn prediction system, the following were used:

Streamlit (version 1.35.0), Pandas (version 1.5.3), Joblib (version 1.2.0), Scikit-learn (version 1.2.2), Imbalanced-learn (version 0.10.1), Openpyxl (version 3.1.2), Serialization of models with Python Pickle files.

Chapter 3
Conducted experiments and obtained results

3.1 Methodology of the conducted experiments

Our research hypothesis according to the purpose of the system is as follows:

"It is possible to develop a system that uses a real database, applied daily by managers in a telecommunications operator, to reliably predict subscriber churn, and which demonstrates high values for key parameters, including accuracy, sensitivity, precision and F1-score. This system will be not only statistically optimal, but also practically applicable in real business scenarios, where the diversity of data and dynamic conditions require flexible management of customer retention processes."

Within the framework of the conducted experiments, the effectiveness of various predictive models was evaluated to establish which machine learning technique provides the best results in predicting customer churn. This evaluation included an in-depth analysis of key model parameters, which contributed to both the validation of the hypothesis and the development of an effective system for managing the business customer retention process. This approach resulted in the

creation of a reliable and practical solution that not only predicts customer churn with high accuracy, but also supports customer retention strategies in real-world conditions.
The experiments conducted followed the sequence described in Chapter 2:
The effectiveness of the churn prediction models was evaluated using a set of widely recognized criteria, including accuracy, sensitivity, F1-score, and precision.
In order to ensure the best performance of the models and to guarantee their practical applicability in the system, we conducted multiple evaluation cycles. Our main goal was to select a model that not only demonstrated high accuracy, but also showed adaptability to different conditions and data types. Therefore, we approached the problem by testing the models on two different data sets – one with preprocessing applied and one without.
This comparison approach allowed us to select the best model that combines high accuracy on processed data and robustness on raw data, thus providing a practical and reliable solution for real-world deployment.

3.2 Experimental Results

The initial unstructured dataset was processed to make it suitable for machine learning by balancing classes, standardizing features, and splitting the training and validation data.
We used the Standard Scaler from the scikit-learn module to normalize the data, providing a standard variance and a mean of 0. This allowed models such as Support Vector Machines (SVM) and Logistic Regression to treat features equally. Using SMOTE (Synthetic Oversampling Technique), we balanced the class, which improved the accuracy and robustness of the models in identifying churn customers. The data was divided into a test and training set, after which the machine learning algorithms were applied and evaluated on key performance indicators.

3.2.1 Results without preprocessing

The models demonstrated different levels of performance–table 2.

Model	Accuracy	Precision (No Churn)	Precision (Churn)	Recall (No Churn)	Recall (Churn)	f1-Score (No Churn)	f1-Score (Churn)
Logistic Regression	**95%**	**0.95**	**0**	**1**	**0**	**0.97**	**0**
Na¨ıve Bayes	**86%**	**0.95**	**0.10**	**0.90**	**0.20**	**0.93**	**0.13**
Random Forest Classifier	**95%**	**0.95**	**0**	**1**	**0**	**0.97**	**0**
AdaBoost + Decision Tree	**95%**	**0.95**	**0**	**1**	**0**	**0.97**	**0**

Extra Trees Classifier	**94%**	**0.95**	**0**	**0.99**	**0**	**0.97**	**0**
Decision Tree	**89%**	**0.95**	**0.12**	**0.93**	**0.17**	**0.91**	**0.14**
Support Vector Machine	**95%**	**0.95**	**1**	**1**	**0.01**	**0.97**	**0.02**
AdaBoost + SVM	**95 %**	**0.95**	**0.00**	**1.00**	**0.00**	**0.97**	**0.00**
LDA	**95 %**	**0.95**	**0.00**	**1.00**	**0.00**	**0.97**	**0.00**

Table 2. *Results without preprocessing*

The conclusions from the analysis of churn prediction models show that while many of them demonstrate high accuracy in classifying the predominant "No Churn" class, most encounter significant difficulties in identifying the key "Churn" class. This includes models such as Logistic Regression, Random Forest Classifier, SVM, Extra Trees, LDA and AdaBoost which showed high overall accuracy but lacked sensitivity to the positive class.

Models such as Naive Bayes and Decision Tree offer a slightly better trade-off between accuracy and sensitivity, but are still far from satisfactory performance.

This highlights the challenge associated with imbalanced classes and the difficulty of correctly predicting the rare but critical class of customers at risk of churn. Classifying the minority class is key to predicting churn and to successfully using the model in a subscriber churn prediction system. Without a reliable prediction of the positive class ("Churn"), the system would be ineffective, as it would not be able to perform its main function – timely identification of customers at risk of churn.

3.2.2 Results with preprocessing

Before applying the machine learning algorithms, the data underwent extensive preprocessing, which included important steps such as normalization of values using the Standard Scaler and application of the Synthetic Method for Increasing Minority Classes (SMOTE). These methods were used to ensure a more even distribution of the data and to eliminate potential imbalances that could negatively affect the performance of the models. Preprocessing had a dramatic impact on the performance of the model, leading to a significant improvement in the accuracy and stability of the predictions. As illustrated in Table 3, the results clearly show that the model performance is significantly higher after applying these preprocessing techniques, which highlights the importance of optimal data preparation before the training phase.

Model	**Accuracy**	**Precision (No Churn)**	**Precision (Churn)**	**Recall (No Churn)**	**Recall (Churn)**	**f1-Score**	**f1-Score (Churn)**

						(No Churn)	
Logistic Regression	**54%**	**0.53**	**0.56**	**0.65**	**0.44**	**0.58**	**0.49**
Na¨ıve Bayes	**54%**	**0.53**	**0.56**	**0.65**	**0.44**	**0.58**	**0.49**
Random Forest Classifier	**95%**	**0.94**	**0.96**	**0.96**	**0.94**	**0.95**	**0.95**
AdaBoost + Decision Tree	**83%**	**0.80**	**0.87**	**0.88**	**0.78**	**0.84**	**0.82**
Extra Trees Classifier	**95%**	**0.96**	**0.94**	**0.94**	**0.96**	**0.95**	**0.95**
Decision Tree	**91%**	**0.92**	**0.91**	**0.90**	**0.93**	**0.91**	**0.92**
Support Vector Machine	**59%**	**0.56**	**0.65**	**0.79**	**0.39**	**0.65**	**0.49**
AdaBoost + SVM	**55%**	**0.54**	**0.56**	**0.56**	**0.54**	**0.55**	**0.55**
LDA	**55%**	**0.53**	**0.56**	**0.65**	**0.44**	**0.59**	**0.50**

Table 3. *Results with preprocessing*

The analysis showed that preprocessing significantly improves the performance of the models, especially for ensemble methods and tree-based classifiers. The Random Forest Classifier and the Extra Trees Classifier showed excellent accuracy of 95% and balanced values of precision, sensitivity and F1-score for both classes. These models have proven to be highly effective for real-world applications. AdaBoost with Decision Tree also achieved good results with an accuracy of 83%, demonstrating reliable recognition of the "No Churn" customers, but with slightly lower sensitivity for the "Churn" class. The Decision Tree, with an accuracy of 91%, showed a balanced performance.

3.3 Comparison and Analysis of Results

Preprocessing of data has a significant impact on the performance of models, contributing to increased sensitivity, precision, and F1-score, especially for ensemble methods such as Random Forest Classifier and Supplementary Tree Classifier. These techniques help to achieve balanced results between the two classes, which is critical for our customer churn prediction task, where accurate identification of customers with a high risk of churn is required. Better recognition of these customers is essential for effective planning of retention strategies.

Random Forest and Supplementary Tree classifiers achieved high accuracy of 95%, significantly outperforming models such as Logistic Regression and Naive Bayes. AdaBoost combined with Decision Tree also demonstrated impressive results with an accuracy of 83%. This shows that ensemble approaches are more robust and reliable in identifying customers at risk of churn, especially when data is supplemented with techniques such as SMOTE.

ROC Curve Analysis

Based on the comparative analysis of the models, the ROC curves provide a clear visualization of the impact that preprocessing has on the performance of the models.

According to the ROC analysis, preprocessing significantly improves the discriminative power of ensemble techniques such as Random Forest Classifier and Supplementary Tree Classifier, which achieve values of 0.99 and almost perfect AUC scores after preprocessing. This finding is consistent with the results in Tables 2 and 3, which show that these models demonstrate high precision, sensitivity, and F1-scores for the different classes - Figure 6.

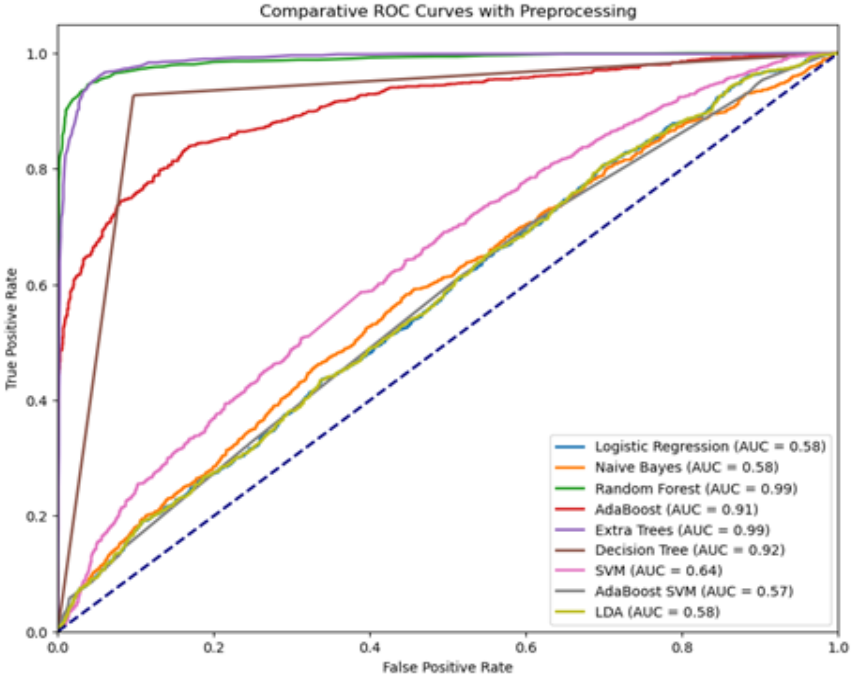

Figure 6. *Comparison of ROC curves with preprocessing*

3.4. Conclusions

The results obtained from the conducted experiments confirmed the research hypothesis that it is possible to develop a system that uses a real database, used daily by managers in a telecommunications operator, to reliably predict subscriber churn. The system demonstrates high values for key parameters, including accuracy, sensitivity, precision and F1-score.

The system is not only statistically optimal, but also practically applicable in real business scenarios, where the diversity of data and dynamic conditions require flexible management of customer retention processes. The results of the experiments showed that with appropriate data preprocessing and integration of ensemble methods such as Random Forest Classifier and Supplementary Tree Classifier, the system offers stable and reliable predictions. These models

showed the highest values for all key indicators, achieving an accuracy of 95%, sensitivity and precision balanced for both the positive and negative classes. These ensemble models have demonstrated robustness and reliability, especially on pre-processed data and in the presence of class imbalance, making them suitable for practical application in a business environment.

The system, based on ensemble models and using a real database, provides reliable forecasts, which are essential for successful customer base management.

3.5 Directions for Future Development

The next steps in the development of the proposed system include the study of more advanced ensemble models, as well as the integration of neural networks, which can further improve the accuracy and ability to identify customers with a high risk of churn. Figure 7 presents a model of a dynamic customer churn prediction system for a telecommunications company, implemented as a software as a service (SaaS). The telecom's information system generates a dataset of business customers with expiring contracts, which is structured in JSON format. Using the JSON-RPC protocol, this dataset is transmitted to the dynamic customer churn prediction system, which is implemented as a cloud service on one of the major platforms, such as AWS or Azure. The prediction system analyzes the data and generates a new set of customers who are at high risk of churn. The output from the system, containing the identified customers with a probable churn, is returned back to the telecom's information system via the JSON-RPC protocol. Implementing such a system as SaaS has a number of advantages, including easy maintenance, scalability and the ability to integrate with other telecom systems, fast and efficient scaling of the system when increasing data volume and load, ensuring stable performance even with a large number of customers. This makes the solution extremely suitable for large telecommunications companies.

Finally, future development of the system may include additional functions for personalizing forecasts according to individual customer characteristics and adding self-learning algorithms that will allow the system to automatically adapt to new data and trends.

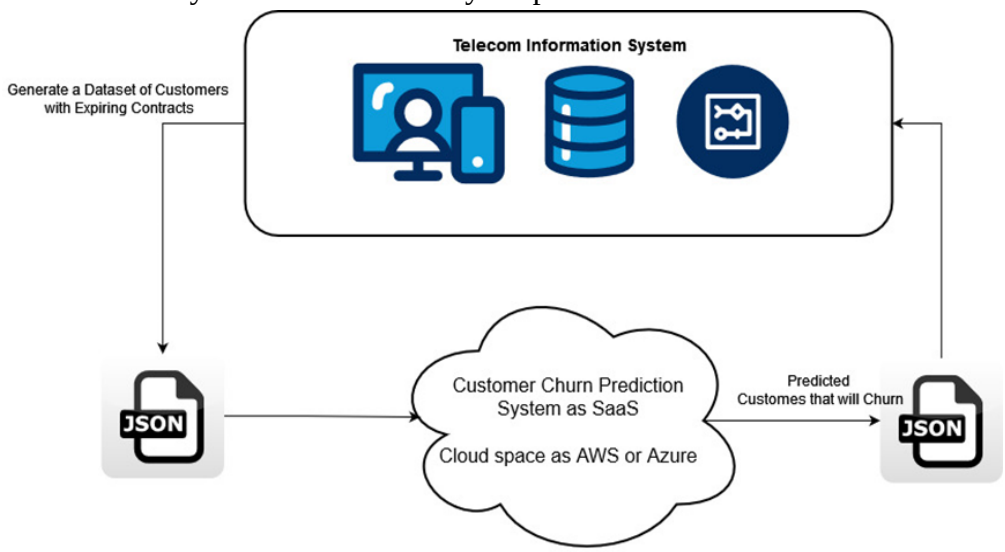

Figure 7. *Dynamic customer churn prediction system from a telecommunications company presented as a software as a service (SaaS)*

SCIENTIFIC AND PRACTICAL CONTRIBUTIONS

1. The SMOTE method was applied and studied for preprocessing data from a real database containing 8,453 records of business customers from a leading telecommunications operator in Bulgaria. This addressed the issue of class imbalance and demonstrated improved prediction accuracy for the machine learning models used.

2. An experimental study was conducted on various machine learning models, including:

- Logistic Regression
- Naive Bayes
- Random Forest Classifier
- ADABOOST with Decision Tree
- Extra Trees Classifier
- Decision Tree
- Support Vector Machine
- ADABOOST and Support Vector Machine
- Linear Discriminant Analysis

The efficiency and accuracy of these models were evaluated in predicting the two main classes—"churn" and "non-churn." Based on the analysis, the most suitable algorithms for customer churn prediction were identified.

3. A classification of business processes in the telecommunications industry was proposed, systematizing key aspects and their interrelationships. This facilitates the identification of primary areas for improvement.

4. Analysis of the Business Customer Retention process: An in-depth analysis of the Retention process was conducted, revealing the main factors influencing customer loyalty and retention. Interviews were conducted with participants in the process.

5. Business Customer Retention Process Redesign: A new process design has been developed to optimize customer interaction and increase the effectiveness of retention strategies.

Applied Contributions

1. Comprehensive Review of Technology-Based Solutions: A detailed analysis of existing technology solutions for business process management in the telecommunications sector has been prepared, which provides a basis for a better understanding of current practices and innovations in the industry.

2. An appropriate system architecture has been justified and selected, which provides flexibility and efficiency in data processing and customer churn forecasts.

3. A detailed system design has been prepared, which includes a description of the main components and functionalities necessary for its effective functioning.

4. Development of a system prototype: A working prototype of the system was created, demonstrating the applicability of the proposed solutions and concepts in a practical environment.

PUBLICATIONS

The main theoretical and applied results of the dissertation are presented in 3 publications:

1. Bekyarova-Tokmakova, A., Mileva, N., & Tokmakov, D. (2021). Classification of business processes in telecommunications. In Proceedings of the 2021 29th National Conference with International Participation (TELECOM) (pp. 153–156). IEEE. https://doi.org/10.1109/TELECOM53156.2021.9659690

Scopus, Web of science

2. Bekyarova-Tokmakova, A., & Mileva, N. (2024). Analysis of the retention process of business customers in the telecom industry. In Proceedings of the 2024 XXXIII International Scientific Conference Electronics (ET). IEEE. https://doi.org/10.1109/et63133.2024.10721509

Scopus

3. Bekyarova-Tokmakova, A. (2023). Applications of artificial intelligence in customer-related processes in the telecommunications industry. **Scientific papers of the Union of Scientists in Bulgaria–Plovdiv** , series B. Natural and Human Sciences, vol. XXIV, ISSN 1311-9192 (Print), ISSN 2534-9376 (On-line), 2023https://usb-plovdiv.org/wp-content/uploads/2023/06 /2023_natural_sciences_and_humanities_vol_XXIV.pdf#page=166