<u>HIGHER SCHOOL FOR INSURANCE AND FINANCE - SOFIA</u>

Department of „Finance and Insurance“

AUTHOR’S ABSTRACT

OF THE DISSERTATION

Impact of financial technologies on the management of credit risk in banks

for the award of the educational and scientific degree „Doctor” under the doctoral program „Finance, Insurance and Social Insurance” in the professional field 3.8. Economics

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The dissertation was reviewed and admitted for defense at a meeting of the Department of „Finance and Insurance“ at the Higher School of Insurance and Finance (VUZF University), held on April 2, 2025.

The dissertation has a total volume of 213 printed pages. It is structured into an introduction, three chapters, a conclusion, a list of references (including a total of 149 sources in Bulgarian and English), and appendices. The dissertation contains 27 figures and 6 tables.

The defense of the dissertation will take place on June 13, 2025, at 11:00 a.m.

I. GENERAL CHARACTERISTICS OF THE DISSERTATION

The relevance and significance of the research stem from the growing impact of financial technologies on risk management in banks, and more specifically on credit risk, as well as their potential to completely revolutionize the way it is assessed and managed. Banks operate in an environment that is becoming increasingly complex and dynamic. The modern financial environment is further complicated by the globalization of markets, which exposes banks to international economic, political, and regulatory risks. Events such as the 2008 financial crisis and the COVID-19 pandemic have demonstrated how quickly instability in one part of the world can spread and affect the entire world. This interconnectedness means that banks must have effective tools for forecasting and managing credit risk, enabling them to respond adequately to changes in the global economy. Against the backdrop of a complex economic environment, banks are also facing the expansion and intensification of competition within the financial sector. Traditional banks are no longer the sole providers of financial services – the market is increasingly populated by fintech companies and neobanks offering fast and convenient alternatives to traditional banking. These new players are often more flexible and innovative, which makes them attractive to consumers, especially among the younger generation. Heightened competition forces banks to offer more attractive credit conditions and to take on greater risks to retain their clients, which further amplifies the importance of effective credit risk management. In this context, financial technologies offer innovative solutions that can help banks improve credit risk management, adapt to new challenges, and maintain their stability in a rapidly changing environment.

The relevance and significance of the chosen topic are also evidenced by the numerous international scientific conferences organized on the subject. Issues related to the chosen topic are becoming more and more numerous and are attracting the attention of both the banking sector and the academic community. The topic is extremely significant for both financial theory and financial practice, which is why it is the subject of this dissertation. The ultimate goal of the dissertation is to serve as a starting point for both theorists and practitioners.

The object of the research in the dissertation will be the commercial banks in Bulgaria.

The subject of the research is credit risk management and the opportunities offered by modern financial technologies for its improvement. The research also focuses on the challenges and risks that may arise from the use of these technologies and on ways to overcome them.

The purpose of the dissertation is to provide an in-depth and objective scientific study with clearly defined objectives:

- To define the essence of financial technologies and their application in the context of credit risk management;
- To systematize the stages of credit risk management and analyze the opportunities for their improvement through the integration of modern financial technologies;
- To examine the opportunities and risks associated with the application of modern financial technologies in credit risk management.
- To investigate and identify the factors influencing the share of non-performing loans at leading commercial banks in Bulgaria;
- To examine the relationship between the application of financial technologies and the fulfillment of ESG;
- To formulate recommendations regarding the application of financial technologies in the credit risk management of banks.

The main tasks of the research, aimed at achieving the set objectives of the dissertation, include:

- To analyze the development of the theory and principles of credit risk and banking regulation;
- To define what financial technologies are and their application in the context of credit risk management;
- To determine the stages of credit risk management and the possibilities for their improvement;
- To explore the opportunities provided by financial technologies in credit risk management, as well as to analyze the challenges arising from their use and the ways to overcome them.
- To develop econometric models to assess the key factors influencing the share of non-performing loans, from both a microeconomic and a macroeconomic perspective;
- To investigate the relationship between the application of financial technologies and the fulfillment of ESG principles;
- To formulate recommendations regarding the application of financial technologies in the credit risk management of banks.

The dissertation **defends the thesis** that financial technologies are becoming a significant factor for the successful management of credit risk in commercial banks. Through the integration of modern financial technologies, banks improve their processes, which in turn leads to a reduction in credit risk.

For the purposes of the research, the following hypotheses have been formulated:

Hypothesis 1: The application of financial technologies enables banks to improve the processes of credit risk management and consequently, reduce non-performing loans.

Hypothesis 2: Financial technologies have the potential to significantly transform credit risk management in banks through process automation, advanced data analysis and innovative models.

Hypothesis 3: The improper application of financial technologies poses significant risks to banks, which may lead to an increase in risk levels.

The methodology applied in the development of the dissertation consists of:

- *Theoretical analysis – based on theoretical analysis, the essence of credit risk management, banking regulation, and financial technologies, as well as their interrelations, is examined;*
- *Historical-logical approach – allows the identification of characteristics, differences, and new trends in the management and regulation of credit risk over different time periods;*
- *Comparative analysis – used to highlight the similarities and differences between traditional models of credit risk management and models based on financial technologies;*
- *Hypothetico-deductive method – applied in the formulation of research hypotheses, which are subject to confirmation or rejection;*
- *Descriptive analysis – used to identify the stages of credit risk management in commercial banks in Bulgaria;*
- *Statistical analysis – analyzes key performance indicators of a portion of the banking sector in Bulgaria to establish the benefits of applying financial technologies in credit risk management;*

- *Econometric modeling – applied for the empirical identification and assessment of the impact of various factors on the share of non-performing loans.*

For the realization of the dissertation, the existing academic literature on the topic has been analyzed. Studies by leading credit institutions worldwide on the effects of the application of financial technologies on credit risk management have also been examined. The regulatory framework of credit risk management has been studied as well. Sources of information also include international institutions such as the European Central Bank, the World Bank, and others. In the dissertation, econometric models have been developed to assess the factors influencing the share of non-performing loans from both a microeconomic and a macroeconomic perspective. The application of both approaches is important for a comprehensive assessment of the factors influencing non-performing loans, as it contributes to the subsequent development of complex solutions that reflect both the internal policies of banks and the macroeconomic environment in which they operate. For the econometric modeling and subsequent evaluation, the specialized open-source software Gretl has been used. In addition, standardized interviews with experts and heads of credit risk management departments have been conducted to obtain more in-depth information about the application of financial technologies in their activities. The interviews were conducted based on a standardized methodology that included a structured questionnaire. The main questions in the interviews broadly cover: the overall use of defined financial technologies in credit risk management, assessment of their effectiveness and profitability, identification of risks and challenges in their application, and anticipated future trends. In support of the analysis, publicly available information from the websites of the researched credit institutions has also been collected regarding the application of financial technologies in credit risk management processes. For the automated extraction of data from these websites, the web scraping method was employed, using a specially developed script. This method was chosen due to the need for efficient collection of a large volume of publicly available information from the websites of the surveyed credit institutions. Web scraping enables the automated extraction of structured data, which would otherwise require significant time for manual processing. The process of applying web scraping includes predefined criteria for searching keywords and phrases that contain information about the applied financial technologies. After the data collection was completed, the data were manually reviewed for accuracy verification and processed for inclusion in the analysis. The script was developed in the **Visual Studio Code** environment, which is an integrated development environment (IDE) widely used for writing, testing, and debugging programming code. The scripts are written in the **Python** programming language, with the main libraries used being:

- **Selenium** – for automating interaction with web pages and handling dynamically loaded content;
- **Pandas** – for structuring, filtering, and performing statistical processing of the extracted data;
- **The BeautifulSoup** library was also used when necessary.

In accordance with ethical considerations, data collection was limited solely to publicly available web pages. The publicly available information collected, together with the information from the interviews with experts from the studied banks, enables a comprehensive and objective study of the application of financial technologies in credit risk management in banks.

II. Structure and content of the dissertation

The structure of the dissertation consists of: an introduction, three chapters, a conclusion, a list of references, and appendices.

The introduction outlines the relevance and importance of the research topic. It defines the object and subject of the research. The purpose of the dissertation and the main tasks that need to be accomplished to achieve this purpose are specified. The thesis and hypotheses subject to confirmation or rejection are formulated. The methodology to be applied in the development of the dissertation is also defined, and the structural plan of the work is presented.

Chapter One of the dissertation includes an analysis of the theoretical and historical aspects of credit risk and banking regulation. It defines the essence of the term "financial technologies" and classifies the main groups of financial technologies. A comprehensive concept of credit risk management is presented, and the possibilities for the integration of financial technologies in this context are explored.

Chapter Two of the dissertation contains a detailed study of the opportunities and challenges that may arise for banks from the application of each of the specified technologies in credit risk management. It also analyzes the similarities and differences between modern financial technologies and traditional statistical methods, aiming to present an optimal combination for improving processes. Recommendations are made for the successful integration of financial technologies into the credit risk management of banks.

Chapter Three of the dissertation involves the development of econometric models for assessing the leading factors influencing the share of non-performing loans. In this context, the relationship between expenditures on software products and technologies and the size of non-performing loans in the respective credit institution is evaluated. The interpretation of the results obtained from the developed econometric models is provided. Additionally, the relationship between the application of financial technologies and ESG fulfillment is examined, along with the challenges and opportunities presented to banks.

The conclusion presents a summary of the main findings from all chapters and summarizes the results of the hypothesis testing.

The list of references and appendices can be found at the end of the dissertation.

III. Synthesized presentation of the dissertation

CHAPTER I. CONCEPTUAL FRAMEWORK OF CREDIT RISK MANAGEMENT AND FINANCIAL TECHNOLOGIES

Theoretical aspects of credit risk and banking regulation

The banking sector is considered a fundamental pillar of the economy and a driving force behind its growth, playing a key role in the economic stability of every country. It is the interconnection that keeps the economy functioning, as it provides loans and allows businesses and households to save, invest, and increase spending, ultimately sustaining economic growth. Without access to credit, the economy would be "paralyzed," as there would be no necessary financial resources for businesses and households, thus slowing down economic activity. On the other hand, without banks, the economy would not be able to function, as there would be no effective mechanism for managing financial flows, risk, and monetary policy.[1] In this context, one of the greatest risks that could disrupt the balance in the banking sector is credit risk. Since credit exposures have the highest relative share in banks' assets, credit risk can be defined as the most significant risk in banks' portfolios. According to the Basel Accords, credit risk is defined as the risk that a borrower or counterparty will fail to meet their obligations under the agreed terms.[2] There are also other similar interpretations by researchers regarding credit risk. Greuning & Bratanovic define credit risk in their study titled „Analyzing Banking Risk: A Framework for Assessing Corporate Governance and Risk Management" as „the chance that a debtor or issuer of a financial instrument - whether an individual, company, or government - will fail to repay the principal and other cash flows associated with the investment under the terms specified in the credit agreement".[3] In general, credit risk can be defined as the risk that a debtor will fail to meet their credit obligation. The reasons for the existence of credit risk are diverse and can be summarized into two main categories of factors - internal and external.

[1] Naili M. & Lahrichi Y. (2022). The determinants of banks' credit risk: Review of the literature and future research agenda. International Journal of Finance & Economics. 27:334–360. [online], available at: < https://doi.org/10.1002/ijfe.2156 [Accessed 14 January 2024];

[2] Basel Committee on Banking Supervision (2000). Principles for the Management of Credit Risk, BIS, [online], available at: https://www.bis.org/publ/bcbs75.htm [Accessed 23 May 2023];

[3] Greuning, H. & Bratanovic, S. (2020). Analyzing Banking Risk: A Framework for Assessing Corporate Governance and Risk Management, 4th ed. Washington, DC: World Bank. [online], available at: < doi:10.1596/978-1-4648-1446-4. License: Creative Commons Attribution CC BY 3.0 IGO, [Accessed 23 May 2023];

Internal factors of credit risk are related to the characteristics of the borrower and the internal banking processes and strategies applied by the credit institution in granting and managing loans. External factors of credit risk are linked to the macroeconomic, political, and social environment in which both the borrower and the credit institution operate, and are often beyond the control of banks. In the banking sector, a significant portion of losses arises precisely as a result of borrowers' failure to fulfill their obligations. Successful credit risk management has always represented a serious challenge, as inaccurate assessment and mitigation of credit risk has been the cause of more than one bank failure, both during systemic financial crises and in cases of individual problems.[4] Due to the nature of their activities and the specific characteristics associated with credit risk, banks face constant challenges, the successful overcoming of which depends largely on the existence of well-developed and effective policies, procedures, and practices for its proper management.

Credit risk can be defined as a complex and multifactorial problem that requires careful analysis and management from both lenders and borrowers. ***Credit risk management is closely intertwined with banking regulation, as regulatory requirements often establish the framework within which banks must manage their risks.***

Banking regulation can be defined as a set of laws, rules, guidelines, and standards established by national and international regulatory bodies aimed at ensuring the stability, transparency, and sustainability of the banking system. It includes supervision of banking activities, control of capital requirements, risk management, and protection of depositors' interests. The necessity of regulating banking activities is determined by their critical importance to economic development and the need to provide reliable protection to economic agents. The primary purpose of banking regulation is to establish optimal, internationally accepted standards for the operations of banks.[5]

There are various theories related to the existence and necessity of banking regulation. These theories are not mutually exclusive but rather explain different aspects associated with banking regulation. They consider both market imperfections and potential risks associated with the regulators themselves. Examples include: the public interest theory, the contractual theory, the asymmetric information theory, the regulatory capture theory, the financial instability theory, and the supervisory capitalism theory.

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[4] Anachkov, K. (2024). Revolutionizing credit risk management: The role of artificial intelligence in banking transformation, Proceedings of the Fourth National Student and Doctoral Conference on „Artificial Intelligence and the Transformation of the Economy“, VUZF University, Publishing House „St. Gregory the Theologian“, ISBN 978-619-7622-66-9, pp. 123–132.

[5] Milanova, E. (2014). Regulations and risk management. Sofia: UNWE Publishing Complex, p. 11;

The theories considered, regardless of their perspective, acknowledge that banking regulation is an inevitable mechanism for managing risks, interests, and interactions within the banking sector. Whether they view regulation as a means of protecting the public interest or as a tool for corporate influence, all theories analyze how regulation shapes and responds to economic reality. Over time, with the evolution of economic processes, the emergence of new crises, and the development of innovations, new challenges arise, requiring updates to the theoretical framework. This is a natural process in economic science, where theories are revised and expanded to reflect new realities. In this context, it is important to analyze how the considered theories are reflected in the current practical regulation of the banking sector.

Historical aspects in the development of credit risk management and regulation

Historically, credit risk management in banks has undergone significant evolution. In the earliest stages of banking development, credit risk was assessed through manual processes and subjective judgments. Banks evaluated creditworthiness based on personal relationships and collateral. With the rise of modern banking in the 17th and 18th centuries, credit risk gradually began to emerge as a serious challenge for banks. Financial crises in the late 19th and early 20th centuries - most notably the Panic of 1907 - highlighted the need to transition to more structured and objective methods of risk assessment. Significant progress was achieved during the second half of the 20th century with the introduction of quantitative models and the development of the first credit scoring models. The adoption of the Fair Credit Reporting Act (FCRA) in 1970 further contributed to the establishment of transparent and objective approaches to creditworthiness assessment. With the advent of computer technologies and the growing capabilities for data processing, banks began applying more sophisticated multivariate statistical models. The financial crisis of 2008 revealed serious deficiencies in existing credit risk management practices, particularly regarding high-risk mortgages and the excessive reliance on credit rating agencies. In the last decade, credit risk management in banks has been marked by technological advancement, global challenges, and a growing emphasis on sustainability. Major international banks such as J.P. Morgan, Wells Fargo, Capital One, and others have been actively investing in research and development of non-traditional credit scoring models. Alongside technological progress, the COVID-19 pandemic introduced new changes to credit risk management. The economic consequences of lockdowns, supply chain disruptions, and heightened uncertainty led to a significant increase in default risk for both businesses and households. The challenges posed by the global pandemic served as a real-time stress test for banks. This time, unlike during the 2008 financial crisis, banks demonstrated their ability to successfully manage the challenge and even managed to offer some of the most extensive crisis-response measures in quantitative terms compared to other measures.[6] Stricter regulations, technological advancements, and coordinated actions by governments and central banks played a crucial role in this success. The expected trend for the next decade is that banks will increasingly adopt modern financial technologies in credit risk management. This includes the use of ever more sophisticated technologies for analytics, forecasting, and automation, which can unlock new methods for risk assessment and enhance the financial stability of the respective banks.

Credit risk management is directly linked to banking regulation. In this regard, it is important to examine its development and supervision, as they play a key role in shaping risk management practices within banks. Although the „embryonic forms“ of banking regulation can be traced back to periods before the 19th century, banking regulations at that time were still relatively limited, and banks operated under minimal supervision. It was precisely the bank failures and crises of that era that triggered the need for enhanced regulation aimed at protecting depositors and increasing public confidence in the banking system. The Great Depression of the 1930s proved to be a turning point in the development of regulations, leading to the introduction of deposit protection mechanisms and stricter regulatory measures. Following World War II, a period of stabilization and rapid development of banking systems ensued, supported by coordinated international efforts for economic recovery. The establishment of the International Monetary Fund (IMF) and the World Bank in 1944 laid the foundations of a global financial system that supports the stability and sustainable development of banking institutions. On the national level, the post-war period was characterized by intensified regulation and an increased role of central banks. At the same time, banking services expanded, lending grew, and financial products became more accessible to the general public. The economic boom of the 1950s and 1960s further accelerated these processes. During the 1970s, against the backdrop of increasingly globalized financial markets, the need for international coordination of banking regulation arose. This led to the establishment of the Basel Committee on Banking Supervision (BCBS) in 1974, which developed international standards for the regulation of banking activities. This process gave rise to the so-called Basel Accords - Basel I (1988), Basel II (2004), and Basel III (2010), each of which built on the previous by introducing more precise mechanisms for risk assessment and management, along with stricter capital requirements. The

[6] Anachkov, K. (2022). Impact of the COVID-19 Pandemic on the Economy and the Banking Sector of Bulgaria, Journal Economic and Social Alternatives, ISSN (print): 1314-6556, issue 4, pp. 28-40.;

2008 global financial crisis revealed numerous weaknesses in the existing regulatory framework, prompting the adoption of additional measures. In response to these shortcomings, Basel III was adopted, aimed at strengthening the resilience of the banking sector through higher capital requirements, improved liquidity management, and the limitation of systemic risk. In January 2023, the FRTB standards and Basel III: Finalizing post-crisis reforms also came into force, which some refer to as Basel IV, although this remains an unofficial designation.

It is important to note that digitalization and the fintech revolution have also played a significant role in the development of banking regulation in recent years. Banking regulators are increasingly introducing rules for the regulation of digital assets and raising cybersecurity requirements, as digitalization heightens the risks of hacking and data breaches. Regulators continue to adapt their frameworks to new realities, which include ESG factors and technological innovations. Future prospects are linked to greater integration of financial technologies, stricter requirements for the management of environmental and social risks, and the creation of sustainable financial systems capable of responding to the changing conditions of the global market.

The essence of financial technologies

Financial technologies, or fintech for short, can be defined as new, innovative technologies used by banks and companies aimed at improving and streamlining financial services. Financial technologies can be utilized by both startups and established financial institutions seeking ways to enhance the efficiency of their processes, reduce costs, and deliver higher-quality products to their customers. A turning point for the role of technology in human life was the COVID-19 pandemic, which demonstrated how essential technological development is across various sectors and how necessary it has become in nearly every aspect of daily activities. The impact of financial technologies on the banking industry can be divided into two key aspects: external fintech and banking fintech. **External fintech** refers to financial technologies used outside of banks, such as fintech companies operating independently from traditional banking institutions. These companies, through the application of new technologies, offer innovative and convenient financial services and solutions to consumers and businesses. In recent years, the development of fintech banks has become a major trend in the fintech industry. The primary risks posed by the growth of external fintech to commercial banks include competitive pressure and the spread of technological advancements. To mitigate these risks, traditional banks are increasingly adopting digital transformation strategies and investing heavily in their technological development. The term **banking fintech** is defined as the application of technologies within a credit institution, such as artificial intelligence, blockchain technology, cloud computing, big data analysis, and their respective subdivisions. Banking fintech seeks to modernize and streamline traditional banking practices by encouraging innovation, enhancing efficiency, and ultimately leading to a better customer experience.

In the dissertation, financial technologies in banks are classified into four major groups:

1. ***Artificial Intelligence (AI)***. This technology refers to the replication of human intelligence by machines programmed to think, learn, and make decisions in a manner that resembles human behavior, without reliance on human labor. The term can be used to refer to any machine that demonstrates characteristics of human thinking, such as the ability to learn, adapt, and solve problems. The ideal characteristic of artificial intelligence is its ability to reason and take actions that have the highest likelihood of achieving a specific goal. AI can be broadly categorized into subgroups, each with its own focus and application. Some of the key subgroups of artificial intelligence include: machine learning (ML), natural language processing (NLP), robotics, expert systems, voice recognition, and others. Artificial intelligence is increasingly being researched and applied in the financial industry, where it is primarily used to enhance customer service and automate processes. Over the past decade, an increasing number of banks have started investing in and implementing chatbots based on this technology within their operations. Their purpose is to assist customers with inquiries related to accounts, balance checks, transaction histories, loan applications, and general banking information. More advanced chatbots can also provide personalized recommendations, financial advice, and services, aiming to enhance overall customer service. An example of this is J.P. Morgan's 2024 chatbot, powered by generative artificial intelligence, which is connected to improving the process of constructing thematic indexes for institutional investors.[7] The potential applications of AI in the banking sector are vast. The capabilities of this technology have the potential to revolutionize a significant part of banking processes.
2. ***Blockchain***. Blockchain represents a distributed database or ledger shared across the nodes of a computer network. Blockchains are best known for their crucial role in cryptocurrency systems in maintaining a secure and decentralized record of

[7] J.P. Morgan (2024). Quest IndexGPT: Harnessing generative AI for investable indices, [online], available at:< https://www.jpmorgan.com/insights [Accessed 25 January 2025]

transactions, but their use is not limited to cryptocurrency alone. Blockchains can be utilized to make data immutable across various industries.[8] Through blockchain, banks can ensure the secure storage and management of sensitive client data, transaction records, document retention, identity verification, and authentication processes. The use of blockchain also allows for automated contract execution via smart contracts. Additionally, it can streamline identity verification, credit history checks, and financial transaction processing - making credit management more efficient.

3. ***Cloud Computing***. Also known as cloud-based computing, this refers to the delivery of computing services over the Internet. It means that data storage, information processing, and application usage are provided remotely via networks of servers hosted online. This eliminates the need to rely on local servers or personal computers for data storage. The use of cloud computing enables companies to benefit from: greater flexibility, process scalability, enhanced data security, and increased cost-efficiency, by reducing IT infrastructure expenses. Cloud technologies, like those mentioned previously, can also be applied in the banking sector to improve operational efficiency and optimize processes. With cloud services, banks gain access to scalable computing resources capable of analyzing large volumes of credit risk data. This allows for more informed decision-making when assessing a borrower’s creditworthiness. Furthermore, cloud-based solutions offer enhanced data security measures, ensuring that sensitive client information is well-protected.
4. ***Big data***. Big data can be defined as a scientific field that focuses on analyzing, extracting information, studying, storing, and generally working with large and complex datasets that traditional data processing applications are unable to handle. Big data refers to large volumes of structured and unstructured data that grow at high speed and with great variety, involving the use of advanced technologies and techniques that encompass various aspects such as data collection, storage, processing, analysis, and visualization of massive amounts of information. Big data also finds broad application in the banking sector. Banks handle enormous volumes of data on a daily basis, including customer transactions, account information, market trends, and regulatory requirements. By analyzing the data, banks can extract valuable insights that help improve various aspects of their operations.

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[8] Hayes, A. (2023). Blockchain Facts: What Is It, How It Works, and How It Can Be Used, Investopedia, [online], available at: < https://www.investopedia.com/terms/[Accessed 22 October 2023]

Despite the differences and uniqueness of each of these technologies, they are often used together in practice, thereby enhancing various processes. ***The interconnection between different financial technologies creates a stable and efficient ecosystem that strengthens the capabilities of each individual technology.*** Examples of this include the combination of AI-based systems with big data analytics, which improves the accuracy of forecasting and decision-making. Blockchain technology and cloud computing can also be combined to ensure scalable, secure, and efficient transaction processing. The examples provided represent only a small portion of the potential for successfully integrating different technologies.

All four key segments of financial technologies classified in the dissertation have the potential to revolutionize credit risk management in banks. For this reason, it is extremely important to study not only the opportunities but also the risks that arise for banks from their use, in order to accurately assess the effects of their application.

Concept of credit risk management and application of financial technologies in its context

Understanding credit risk management and the traditional practices applied by banks is important for the integration of financial technologies, as it provides valuable context. The stages of credit risk management in commercial banks encompass a comprehensive framework that can be described as follows:

1. <u>Identification and measurement of credit risk.</u> This is the initial step in credit risk management. The main objective at this stage is to prevent potential losses through the early identification of risks.
2. <u>Selection of methods for minimizing credit risk.</u> This process involves multifaceted strategies aimed at reducing potential credit losses. Examples of such strategies include requiring collateral for loans, thereby ensuring that loans are secured by assets.
3. <u>Credit approval.</u> Credit approval can be defined as the critical stage in the credit risk management process, as it is at this stage that the decision is made whether to grant the loan to the respective borrower based on all collected information and the conducted risk assessment.
4. <u>Monitoring of credit risk.</u> At this stage, banks use systems to detect early warning signs that may indicate a credit is becoming problematic.
5. <u>Management of problem loans.</u> In cases where the bank identifies that a loan has become problematic, measures are undertaken, such as an assessment of the borrower's current

situation. Based on the results of this assessment, the bank may implement various corrective actions to manage the problem loan.

6. Regular credit risk reporting. Proper credit risk management requires the generation of regular reports to the bank's governing bodies and all relevant stakeholders, detailing the bank's exposure to credit risk and its compliance with regulatory requirements.
7. Periodic reviews of credit risk policy. It is also important for banks to conduct periodic reviews of their credit risk management policies. These reviews help identify and eliminate weaknesses in existing practices and lead to increased resilience of the respective bank.

Each of the above-mentioned stages of credit risk management is associated with specific challenges, as noted by various scholars. The application of financial technologies offers opportunities to address some of these challenges. The identification and measurement of credit risk are complicated by the need for high-quality and comprehensive data, which is often difficult to obtain or incomplete. Factors such as changing economic conditions and borrower behaviour further complicate the identification process. Accurate identification requires advanced data analysis and continuous monitoring to capture dynamic risk factors—capabilities that modern financial technologies can provide. The methods used to minimize credit risk are also accompanied by various challenges. In addition to fundamental difficulties related to the loan approval process, banks are also striving to eliminate subjective decision-making. Many studies suggest that Big Data analytics and the advanced algorithms offered by modern financial technologies can also help minimize human error and bias. Following the approval of the loan and disbursement of funds to the borrower, banks are expected to conduct regular monitoring, which itself presents diverse challenges. In recent years, banks have increasingly emphasized the transition from a traditional passive monitoring approach to a modern dynamic credit risk monitoring framework, characterized by a robust Early Warning System (EWS). This shift entails moving toward a data-driven systematic approach, which includes forecasting future borrower behaviour and reducing false positives through more sophisticated models and continuous learning.[9] The significant processing and analytical capacity provided by fintech-based technologies allows banks to overcome some of the shortcomings of standardized approaches. Relying solely on traditional methods and failing to integrate modern financial technologies in credit risk management may result in ineffective credit policies. The lack of integration with modern analytical tools, such as those based on artificial intelligence, limits a bank's ability to detect emerging risks and trends, leading to inaccurate conclusions and

[9] CRISIL (2023). Time to usher in next-gen credit monitoring set-up. [online], available at: < https://www.crisil.com/en [Accessed 14 July 2024];

erroneous decisions. Achieving optimal results in credit risk management requires banks to combine traditional practices with modern financial technologies.

CHAPTER II. APPLICATION OF THE FINANCIAL TECHNOLOGIES IN THE CREDIT RISK MANAGEMENT OF BANKS

Opportunities and challenges for banks in applying AI to credit risk management

Artificial intelligence provides significant advantages in credit risk management by enabling the automation of key processes, improved creditworthiness assessment, and continuous post-loan monitoring. Thanks to its ability to analyse large volumes of both structured and unstructured data, including those from alternative information sources, artificial intelligence allows for much more accurate forecasts of customer credit behaviour. The use of this technology can be particularly beneficial for clients with limited credit histories. In addition, it supports the early detection of potential delinquencies or fraud, enabling banks to respond in a timely manner and make informed decisions aimed at minimizing risk. The application of artificial intelligence also offers a solution to the problem of subjectivity in decision-making by introducing more objective, data-driven approaches to modelling and analysis.

To ensure a comprehensive study, it is essential to analyse the challenges and potential risks that banks may face when applying this technology in their credit risk management, as well as the ways to overcome them. One such risk, which significantly hinders the implementation of more complex models by banks, is associated with the „black box“ problem, where it is not possible to explain how a particular result was reached. In response to this issue, the attention of both the academic community and practitioners has shifted toward the development of Explainable Artificial Intelligence (XAI), which aims to increase the transparency and interpretability of AI-based systems. XAI enables banks to understand how more complex results are generated and allows for the identification of potential errors or anomalies in the models.

In addition to algorithmic risks and the danger of the „black box“, there are other potential risks that may adversely affect the bank's credit activity. Among them are:

- Risk related to data quality and availability. The use of incomplete, outdated, or irrelevant data can lead to inaccurate assessments and poor management decisions. To minimize this risk, banks should implement a comprehensive data management approach, including tools for data cleansing and validation, enhancing data protection levels, integrating multiple information sources, and ensuring continuous monitoring and regular system updates.

- Risk related to model performance issues. To overcome this risk, banks should ensure the continuous training, testing, and validation of their models, while also guaranteeing their adaptability to changing data, regulatory requirements, and technological innovations.
- Risk related to integration with existing models. To successfully overcome this challenge, banks must provide regular system updates and apply a clear, phased integration strategy that ensures compatibility and minimizes potential risks.
- Risk related to cybersecurity. Cybersecurity is also critical, especially considering the volume and sensitivity of the data processed—insufficient protection creates a real danger of breaches and misuse. Effective management of this risk requires conducting information security audits, encrypting data, implementing anomaly detection systems, training staff, and enforcing strict access control to information resources.
- Ethical and social challenges. The improper use of this technology could also create ethical and legal challenges, including the risk of reinforcing biases and violating data privacy rights.

To successfully address the above-mentioned risks and challenges arising from the use of this technology, banks must introduce robust and consistent approaches, clear regulatory compliance strategies, regular model monitoring, and continuous system updates, ensuring transparency and fairness in decision-making. With the right preparation, coordination, and cooperation between various departments, the listed risks can be minimized. The application of this new technology is necessary, as beyond improving credit risk management, the ability to analyse large volumes of information will allow banks to better understand customer needs, shorten the duration of certain processes, and ultimately improve the customer experience.[10]

Use of blockchain technologies and their impact on credit risk management

Blockchain technology initially emerged as a means for conducting and storing transactions, but today its application is significantly broader. Its use offers a number of advantages for credit institutions, with the main ones being enhanced security, reliability, decentralization, and reduced transaction processing time. Although this technology is not specifically designed for credit risk management, its implementation can also lead to improvements in processes by providing greater transparency and traceability of data related to customers' credit histories and identities. Through applications such as digital identification, shared credit information

[10] Anachkov, K. (2024). Opportunities And Challenges For Banks From The Application Of Artificial Intelligence In Credit Risk Management, Proceedings of the Scientific Conference „Innovative Information Technologies for Economy Digitalization", Publishing Complex - UNWE, ISSN 3033-0432 (print), pp. 89–96.;

registries, and automated processes via smart contracts, blockchain technology can also contribute to fraud reduction, increased operational efficiency, and better collateral management within the credit process.

In addition to the positive aspects of applying this new technology, it is important to examine the potential risks and challenges that may arise from its use. The challenges of applying blockchain technology in the banking sector may arise as a result of the lack of global standards, and concerns about compliance with personal data protection legislation. . Additional risks may emerge due to the difficulty of managing incidents resulting from the technology's decentralized nature, and the high energy consumption of certain blockchain protocols. There are also some ethical and social issues related to access to the technology, as well as challenges in ensuring operational interoperability between different blockchain systems and institutional practices.

Addressing the challenges and risks associated with blockchain implementation requires cooperation between credit institutions, regulators, and technology companies. Such cooperation is fundamental to overcoming barriers and minimizing risk. In addition, the use of energy-efficient protocols, the development of internal competencies, and the promotion of ethical principles when handling sensitive information are key to building a sustainable and responsible blockchain model. Through gradual integration, training, and adaptation, blockchain technology can be successfully implemented, providing significant benefits and delivering a competitive advantage to the credit institutions that adopt it.

Application of cloud computing and its effect on credit risk management

Cloud computing is establishing itself as an important technology for credit institutions in terms of the effective management of large volumes of data. It offers significant advantages for credit risk management, including improved real-time data collection and analysis, enhancement of credit scoring models, more accurate fraud detection, and faster decision-making. Moreover, cloud infrastructure provides greater flexibility, scalability, and cost optimization, which allows banks to adapt more effectively to changing market conditions and to respond promptly to risks.

The improper use of cloud computing in credit institutions, as with the other technologies discussed, is associated with various challenges and risks. Among the most prominent are risks related to misconfiguration of the cloud environment, limited control over data, and the sensitivity of financial information. Additional complications arise from legal restrictions regarding data location, as well as increased cybersecurity threats, including unauthorized access and phishing attacks. To minimize these risks, banks should ensure high levels of cryptographic protection, strict service level agreements (SLA) with their providers, regular testing and training, as well as guarantees for infrastructure compatibility and scalability.

Application of big data – opportunities and challenges for banks in managing their credit risk

Large datasets are becoming an increasingly key asset for improving credit risk management in banks. Technological advancements enable banks not only to collect and store data but also to analyse it in order to develop more accurate credit scoring models, including through the use of alternative data sources such as mobile devices and social media. Research on the topic indicates that integrating such data enhances the precision of risk forecasts compared to traditional methods. The application of interconnected analytics platforms will enable banks to make more informed and well-grounded decisions, which will help reduce credit risk and improve financial resilience.

Despite the significant potential of big data to enhance credit risk management, its use is also a source of risks for credit institutions. The main risks include the need for a high level of protection of personal information, significant investments in technological infrastructure, and a shortage of qualified personnel for data analysis. Additionally, the dependence on cloud solutions introduces further requirements for information security and compliance with regulatory standards. The challenges associated with the application of big data in banks can be overcome through targeted investments in cybersecurity, modernization of IT infrastructure, and development of internal expert capacity. Undoubtedly, the existing challenges hinder its implementation, but they can be overcome.

The use of big data is imperative, as it provides numerous opportunities for banks not only in credit risk management but also in many other areas of their operations. Some of these are related to improving strategic planning, enhancing product offerings, cost optimization, improving marketing management, and enhancing transaction management. As a result, the banks that adopt these technologies become more competitive in the market and gain an advantage over other credit institutions that rely solely on traditional data.

CHAPTER III. ASSESSMENT OF THE IMPACT OF THE APPLICATION OF FINANCIAL TECHNOLOGIES IN THE CREDIT RISK MANAGEMENT OF BANKS IN BULGARIA

Applied methodology for building econometric models for evaluating the influence of various factors on non-performing loans

Based on the conducted literature review and the steadily increasing application of financial technologies in credit institutions over the past decade, expectations have emerged regarding the impact of banks' information technology expenditures on the management of their credit portfolios. In a narrow sense, this refers to the relationship between the expenses incurred for software products and technologies and the amount of non-performing loans of the respective credit institution. For the purposes of the study, based on the compiled information database and the descriptive analysis conducted, the following indicators are selected as influencing factors:

- Operating income;
- Operating expenses, excluding personnel expenses;
- Personnel expenses;
- Gross loans and advances;
- Performing loans;
- IT expenses;
- Full Time Equivalent number of personnel;
- Number of branches and offices.

The indicator „non-performing loans“ was chosen as the result value. Available data includes:

- The value of non-performing loans;
- The ratio of non-performing loans.

To analyse the relationships between the factors and the dependent variable, econometric modelling approaches have been applied. This first requires the construction of a theoretical model. According to the scope of the current study, non-performing loans are examined in their dependency on IT expenses, operating expenses, excluding personnel expenses, personnel expenses, operating income, full time equivalent number of personnel, gross loans and advances, performing loans, and number of branches and offices. Accordingly, the mathematical form of the dependency is as follows:

$$NPL_{Sratio} = f(ITE; OpEx_{epe}; PE; OI; FTE; GLA; PLs; NoBo)$$

където:

NPLs	Non-Performing Loans
$NPLs_{ratio}$	The ratio of non-performing loans
ITE	IT Expenses
$OpEx_{EPE}$	Operating Expenses Excluding Personnel Expenses
PE	Personnel Expenses
OI	Operating Income
FTE	Full Time Equivalent number of personnel
GLA	Gross Loans and Advances
PLs	Performing Loans
NoBO	Number of Branches and Offices

At the next stage, a statistical approach has been applied to assess the corresponding empirical model.

In order for the research to be comprehensive, given the nature of the business of credit institutions, it is important to assess not only the internal factors influencing non-performing loans, but also the external ones, such as the macroeconomic environment, as it defines the context in which the respective bank and its borrowers operate. An isolated examination of only internal or only external factors may lead to an incomplete or misleading risk assessment. An integrated approach allows for the study of both groups of factors and is essential for an accurate risk evaluation.

For the purposes of this study, regarding the assessment of the impact of macroeconomic processes on the amount of non-performing loans, the following indicators have been selected as influencing factors:

- Economic growth (change in the GDP Physical Volume Index);
- Consumer Price Index (CPI);

- Unemployment rate;
- Average salary;
- Amount of loans.

As the dependent indicator, the following is selected:

- The ratio of non-performing loans.

The factors and the dependent variable have the following theoretical relationship:

$$NPL_{SRatio}{}^{macro} = f(GDP; CPI; UnEmpl_{rt}; Salary_{rt}; GLA)$$

Where:

$NPLsratio^{macro}$	*Ratio of non-performing loans to total loans, at the national level*
GDP	*Economic growth (index of physical volume of GDP)*
CPI	*Consumer Price Index*
$UnEmpl_{rt}$	*Unemployment rate*
$Salary_{rt}$	*Average salary*
GLA	*Gross Loans and Advances*

At the next stage, a statistical approach has been applied to assess the empirical models.

Methodology of the empirical research

Based on the developed theoretical models concerning the dependence of non-performing loans in each analysed banking institution, as well as the influence of macroeconomic variables on non-performing loans in the economy as a whole, it is necessary to construct econometric models using empirical data.

At the core of econometric analysis lies the classical regression model. In econometrics, all advancements in this area are applied, and new directions are developed in accordance with the specific features and requirements of researching economic phenomena.[11] Modelling of economic processes is recommended to follow these stages:

- ✓ Stage I – Identification of variables. At this stage, each economic phenomenon is represented by a corresponding variable. The outcome phenomenon is described by the dependent (explained) variable, while the influencing factors are represented by

[11] Arkadiev, D. (2000). Econometrics. Stara Zagora, RIK Iskra, p. 32.

independent (explanatory) variables. A theoretical justification for the selection of the factor and dependent variables is required to ensure the adequacy of the model.

- ✓ Stage II – Specification of the model. In this stage of the econometric analysis, it is necessary to determine the form of the relationship between the variables. The choice of the functional form must be supported by theoretical justification, and the expected dependencies between the variables must be clarified.
- ✓ Stage III – Modeling. This stage involves the actual modeling process. Most commonly, it is conducted using the Ordinary Least Squares (OLS) method. In most cases, its application ensures the acquisition of unbiased and efficient parameter estimates as numerical values. This step is typically performed using econometric software.
- ✓ Stage IV – Significance evaluation. The fourth stage of the econometric analysis involves assessing the statistical significance of the model parameters. This is carried out through statistical hypothesis testing of these parameters, using the following hypotheses:

  Null hypothesis H_0: a=0; b=0 the parameters are statistically insignificant, i.e. equal to zero. Any observed deviation from zero is attributed to random factors and errors.

  Alternative hypothesis H_1: $a \neq 0$; $b \neq 0$ the parameters are statistically significant, different from zero; they reflect real relationships between the studied phenomena.

  The testing of statistical hypotheses regarding the parameters of econometric models is primarily based on the Student's t-criterion.

- ✓ Stage V – Diagnostic testing of the model. At this stage, the accuracy and reliability of the constructed model are evaluated through:
  - o Testing for absence of autocorrelation in the residuals. Its presence may lead to misleading results for researchers. The most commonly used method for detecting autocorrelation in the residuals is the Durbin-Watson statistic.[12] This criterion is a hypothesis test:

    Null hypothesis H_0: no autocorrelation;
    Alternative hypothesis H_1: autocorrelation is present.
    The Durbin-Watson statistic is based on an empirical value calculated using the following formula:

[12] Gujarati, D. (2007). Basic Econometrics. New Delhi, Tata McGraw-Hill, p. 98.

$$DW = \frac{\sum_{t=2}^{n}(e_t - e_{t-1})^2}{\sum_{t=1}^{n} e_t^{\,2}},$$

The obtained value is compared with tabulated values to make a decision.

- Test for homoscedasticity, or in other words, the absence of heteroscedasticity. This phenomenon assumes homogeneity in the variance of the residuals. The most commonly applied test is the Breusch-Pagan LM test.[13] It is composed with:

  Null hypothesis H_0: no heteroscedasticity;

  Alternative hypothesis H_1: heteroscedasticity is present.

  The empirical test statistic is:

  $L = \frac{R^2_{\hat{e}_i^2} / k}{1 - R^2_{\hat{e}_i^2} / (n - k - 1)}$; where k is the number of factors.

- Test for normal distribution of the residuals. “This analysis is typically performed using graphical methods. In a correct (adequate) model, the residuals are independent and follow a Gaussian distribution”.[14]

✓ Stage VI – Interpretation of results. Once the model has been evaluated and has passed the necessary diagnostic tests, the next step is to interpret the obtained results.

To build the econometric models from a microeconomic perspective, data was used from the eight largest banks in Bulgaria by asset size as of December 31, 2022, which together account for 82.79% of the total assets in the Bulgarian banking system for that period. These banks are: DSK Bank AD, UniCredit Bulbank AD, United Bulgarian Bank AD, Eurobank Bulgaria AD, First Investment Bank AD, KBC Bank Bulgaria EAD, Central Cooperative Bank AD and Allianz Bank Bulgaria AD. The credit portfolio of the studied banks represents 83.77% of the total loan portfolio of the entire Bulgarian banking system as of December 31, 2022. The empirical analysis is based on annual data for the period from 2015 to 2022 inclusive. Additionally, for the construction of the econometric model related to assessing the impact of macroeconomic factors on the amount of non-performing loans in Bulgaria over the period 2015–2022, annual data from NSI and BNB were used. The econometric modeling and subsequent evaluation were conducted using the open-source specialized software – **Gretl**.

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[13] Dimitrov, A. (2005). Econometrics. Svishtov, D. A. Tsenov Academy of Economics, p. 63.

[14] Noncheva, V. (2010). Discovering knowledge in the data or The useful statistical methods: theory, software, applications. Paisii Hilendarski University of Plovdiv, p. 113.

Results from the constructed econometric models and their interpretation

This section presents the results for each of the reviewed banking institutions, according to the established theoretical model. For each institution, numerous iterations with calculations of models using different combinations of factors were conducted. Some of these included statistically insignificant elements, while others failed to pass the subsequent mandatory evaluations. Only the models with statistically significant factors that have passed the necessary diagnostic tests are presented here:

Results for „UniCredit Bulbank" AD

Based on the numerous calculations performed using various combinations of factors, the following empirical econometric model with statistically significant influencing factors was identified for „UniCredit Bulbank" AD:

$$\ln(NPL_{SRatio}^{UNI}) = -2.534\ln(ITE) - 2.512\ln(OI) - 7.009\ln(PE) + 4.460\ln(FTE) + 6.417\ln(GLA) + e_t$$

The model passes the subsequent tests for homoscedasticity, absence of autocorrelation, and normal distribution of the residuals.

The model shows the following relationships:

- When IT expenses change by one percent, the ratio of non-performing loans changes by 2.534 percent in the opposite direction, assuming the simultaneous influence of other factors.
- When operating income changes by one percent, the ratio of non-performing loans changes by 2.512 percent in the opposite direction, assuming the simultaneous influence of other factors.
- When personnel expenses change by one percent, the ratio of non-performing loans changes by 7.009 percent in the opposite direction, assuming the simultaneous influence of other factors.
- When the FTE number of personnel changes by one percent, the ratio of non-performing loans changes by 4.460 percent in the same direction, assuming the simultaneous influence of other factors.
- When gross loans and advances change by one percent, the ratio of non-performing loans changes by 6.417 percent in the same direction, assuming the simultaneous influence of other factors.

Results for „Eurobank Bulgaria“ AD

Based on the numerous calculations performed using various combinations of factors, the following empirical econometric model with statistically significant influencing factors was identified for „Eurobank Bulgaria“ AD:

$$\ln(NPL_{SRatio}^{Eurobank}) = -0.592\ln(ITE) + 1.171\ln(FTE) + 4.719\ln(GLA) - 5.169\ln(PLs) + e_t$$

The model passes the subsequent tests for homoscedasticity, absence of autocorrelation, and normal distribution of the residuals.

The model shows the following relationships:

- When IT expenses change by one percent, the ratio of non-performing loans changes by 0.592 percent in the opposite direction, assuming the simultaneous influence of other factors.
- When the FTE number of personnel changes by one percent, the ratio of non-performing loans changes by 1.171 percent in the same direction, assuming the simultaneous influence of other factors.
- When gross loans and advances change by one percent, the ratio of non-performing loans changes by 4.719 percent in the same direction, assuming the simultaneous influence of other factors.
- When performing loans change by one percent, the ratio of non-performing loans changes by 5.169 percent in the opposite direction, assuming the simultaneous influence of other factors.

Results for „FIRST INVESTMENT BANK“ AD

Based on the numerous calculations performed using various combinations of factors, the following empirical econometric model with statistically significant influencing factors was identified for „FIRST INVESTMENT BANK“ AD:

$$\ln(NPL_{SRatio}^{FIB}) = -0.068\ln(ITE) - 0.048\ln(OI) - 0.039\ln(FTE) + 3.501\ln(GLA) - 3.555\ln(PLs) + e_t$$

The model passes the subsequent tests for homoscedasticity, absence of autocorrelation, and normal distribution of the residuals.

The model shows the following relationships:

- When IT expenses change by one percent, the ratio of non-performing loans changes by 0.068 percent in the opposite direction, assuming the simultaneous influence of other factors.
- When operating income changes by one percent, the ratio of non-performing loans changes by 0.048 percent in the opposite direction, assuming the simultaneous influence of other factors.
- When the FTE number of personnel changes by one percent, the ratio of non-performing loans changes by 0.039 percent in the opposite direction, assuming the simultaneous influence of other factors.
- When gross loans and advances change by one percent, the ratio of non-performing loans changes by 3.501 percent in the same direction, assuming the simultaneous influence of other factors.
- When performing loans changes by one percent, the ratio of non-performing loans changes by 3.554 percent in the opposite direction, assuming the simultaneous influence of other factors.

Results for „UNITED BULGARIAN BANK" AD

Based on the numerous calculations performed using various combinations of factors, the following empirical econometric model with statistically significant influencing factors was identified for „UNITED BULGARIAN BANK" AD:

$$\ln(NPL_{SRatio}{}^{UBB}) = -5.751\ln(ITE) + 2.520\ln(OI) + 4.392\ln(NoBO) + e_t$$

The model passes the subsequent tests for homoscedasticity, absence of autocorrelation, and normal distribution of the residuals.

The model shows the following relationships:

- When IT expenses change by one percent, the ratio of non-performing loans changes by 5.751 percent in the opposite direction, assuming the simultaneous influence of other factors.
- When operating income changes by one percent, the ratio of non-performing loans changes by 2.520 percent in the same direction, assuming the simultaneous influence of other factors.

- When the number of branches and offices changes by one percent, the ratio of non-performing loans changes by 4.392 percent in the same direction, assuming the simultaneous influence of other factors.

Results for „DSK Bank“ AD

Based on the numerous calculations performed using various combinations of factors, the following empirical econometric model with statistically significant influencing factors was identified for „DSK Bank“ AD:

$$\ln(NPL_{SRatio}{}^{DSK}) = -1.882\ln(OI) + 10.518\ln(GLA) - 9.668\ln\left(PLs\right) + 0.676\ln(OpExEPE) + e_t$$

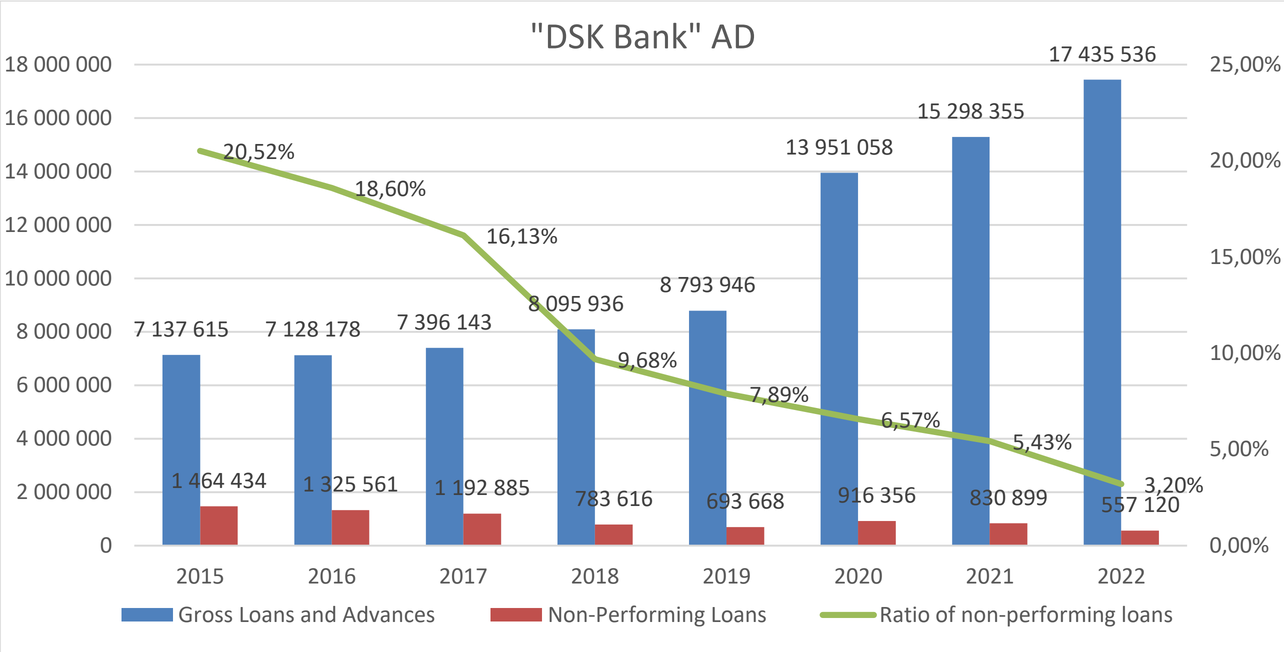
The model passes the subsequent tests for homoscedasticity, absence of autocorrelation, and normal distribution of the residuals.

The model shows the following relationships:

- When operating income changes by one percent, the ratio of non-performing loans changes by 1.882 percent in the opposite direction, assuming the simultaneous influence of other factors.
- When gross loans and advances change by one percent, the ratio of non-performing loans changes by 10.518 percent in the same direction, assuming the simultaneous influence of other factors.
- When performing loans change by one percent, the ratio of non-performing loans changes by 9.668 percent in the opposite direction, assuming the simultaneous influence of other factors.
- When operating expenses, excluding personnel expenses change by one percent, the ratio of non-performing loans changes by 0.676 percent in the same direction, assuming the simultaneous influence of other factors.

IT expenses are not listed as a separate item in the annual financial statements of DSK Bank. However, based on the conducted interview and analysis of publicly available information, it is evident that during the study period, DSK Bank made significant investments and improvements related to the application of technologies aimed at enhancing its credit risk management processes. The bank utilizes machine learning models for credit risk assessment, and in 2022, a new type of algorithm was implemented. The interview revealed that the use of these models led to increased automation in credit approval decisions, resulting in improved efficiency, reduced subjectivity, and consequently, a decrease in the share of non-performing loans.

Figure 21. Dynamics of non-performing loans relative to the total volume of loans in thousands of BGN at „DSK Bank“ AD for the period 2015–2022.



Source: own calculations based on data from the annual financial statements.

As evident from the presented data, the reviewed period shows a significant decline in both the share and the absolute value of non-performing loans, despite the growth in lending.

Results for „KBC Bank Bulgaria“ EAD

Based on the numerous calculations performed using various combinations of factors, the following empirical econometric model with statistically significant influencing factors was identified for „KBC Bank Bulgaria“ EAD:

$$\ln(NPL_{SRatio}{}^{KBC}) = -2.718\ln(GLA) + 3.352\ln(OpExEPE) + e_t$$

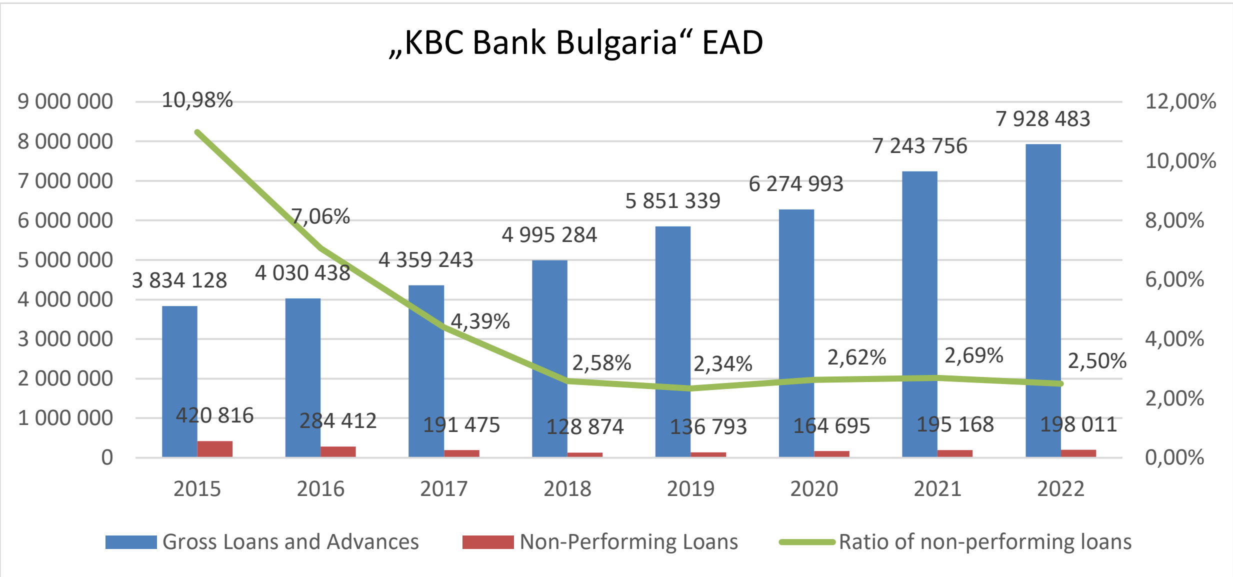
The model passes the subsequent tests for homoscedasticity, absence of autocorrelation, and normal distribution of the residuals.

The model shows the following relationships:

- When gross loans and advances change by one percent, the ratio of non-performing loans changes by 2.718 percent in the opposite direction, assuming the simultaneous influence of other factors.
- When operating expenses, excluding personnel expenses change by one percent, the ratio of non-performing loans changes by 3.352 percent in the same direction, assuming the simultaneous influence of other factors.

IT expenses are not reported as a separate line item in the annual financial statements of KBC Bank Bulgaria for the analysed period. Nevertheless, according to publicly available data and information provided by the Bank, investments were made during this period to improve internal processes and implement modern technologies such as artificial intelligence and big data analytics to enhance customer service and risk management. Since data for IT expenses are not available for KBC Bank Bulgaria, data are presented instead for the dynamics of non-performing loans relative to the total volume of loans in thousands of BGN for the study period 2015–2022, which is shown graphically in the following figure.

Figure 23. Dynamics of non-performing loans relative to the total volume of loans in thousands of BGN at „KBC Bank Bulgaria“ EAD for the period 2015–2022.



Source: own calculations based on data from the annual financial statements.

As evident from the presented data, the reviewed period shows a significant decline in both the share and the absolute value of non-performing loans, despite the growth in lending.

Results for „ALLIANZ BANK BULGARIA“ AD

Based on the numerous calculations performed using various combinations of factors, the following empirical econometric model with statistically significant influencing factors was identified for „ALLIANZ BANK BULGARIA“ AD:

$$\ln(NPL_{SRatio}{}^{ALLIANZ}) = 5.787\ln(PE) - 4.226\ln(PLs) + e_t$$

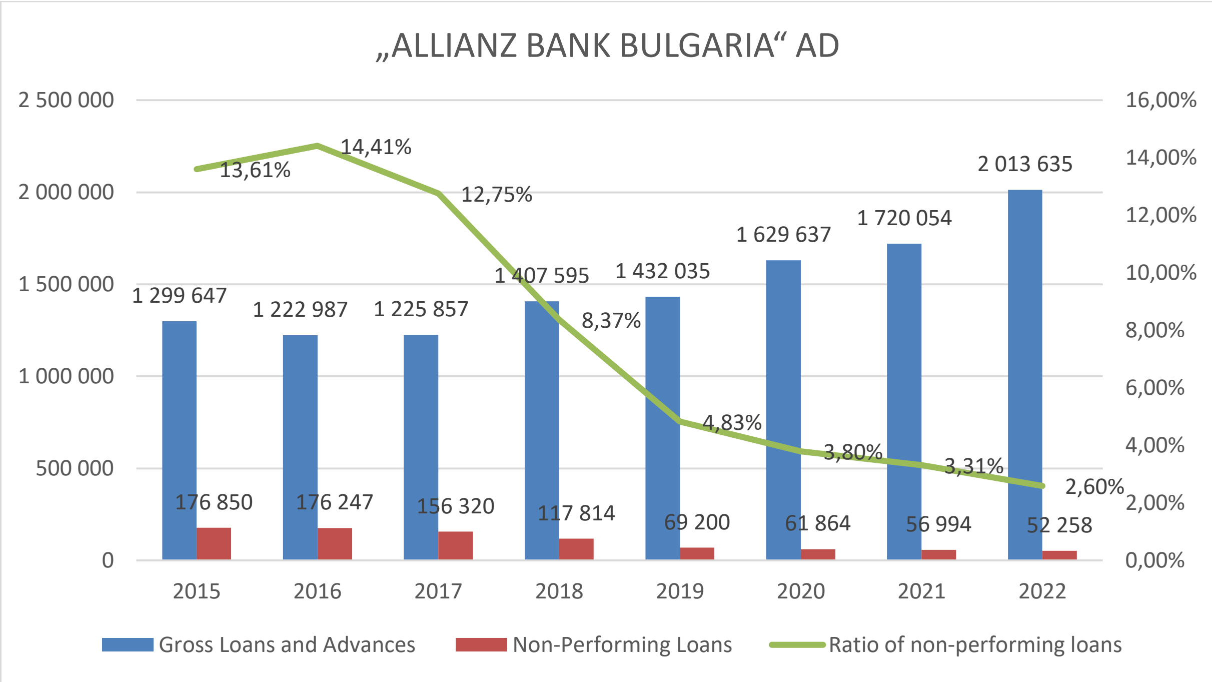
The model passes the subsequent tests for homoscedasticity, absence of autocorrelation, and normal distribution of the residuals.

The model shows the following relationships:

- When personnel expenses change by one percent, the ratio of non-performing loans changes by 5.787 percent in the same direction, assuming the simultaneous influence of other factors.
- When performing loans change by one percent, the ratio of non-performing loans changes by 4.226 percent in the opposite direction, assuming the simultaneous influence of other factors.

IT expenses are not reported as a separate line item in the annual financial statements of ALLIANZ BANK BULGARIA for the analysed period. However, based on the conducted interview and publicly available information, it is evident that the Bank has invested in improving credit risk management processes. Since 2012, the Bank has been using machine learning algorithms to generate the Probability of Default (PD) indicator, and enhancements have been made over the years. Additionally, the Bank maintains a big data warehouse for the purposes of risk management and reporting. During the study period, several updates were made in the area of credit risk management. Since data for IT expenses are not available for ALLIANZ BANK BULGARIA, data are presented instead for the dynamics of non-performing loans relative to the total volume of loans in thousands of BGN for the study period 2015–2022, which is shown graphically in the following figure.

Figure 25. Dynamics of non-performing loans relative to the total volume of loans in thousands of BGN at „ALLIANZ BANK BULGARIA“ AD for the period 2015–2022.



Source: own calculations based on data from the annual financial statements.

As evident from the presented data, the reviewed period shows a significant decline in both the share and the absolute value of non-performing loans, despite the growth in lending.

Results for „CENTRAL COOPERATIVE BANK“ AD

Based on the numerous calculations performed using various combinations of factors, the following empirical econometric model with statistically significant influencing factors was identified for „CENTRAL COOPERATIVE BANK“ AD:

$$\ln(NPL_S{}^{CCB}) = -1.018\ln(\mathrm{FTE}) + 15.506\ln(GLA) - 15.612\ln\left(PLs\right) + 3.505\ln(NoBO) + e_t$$

The model passes the subsequent tests for homoscedasticity, absence of autocorrelation, and normal distribution of the residuals.

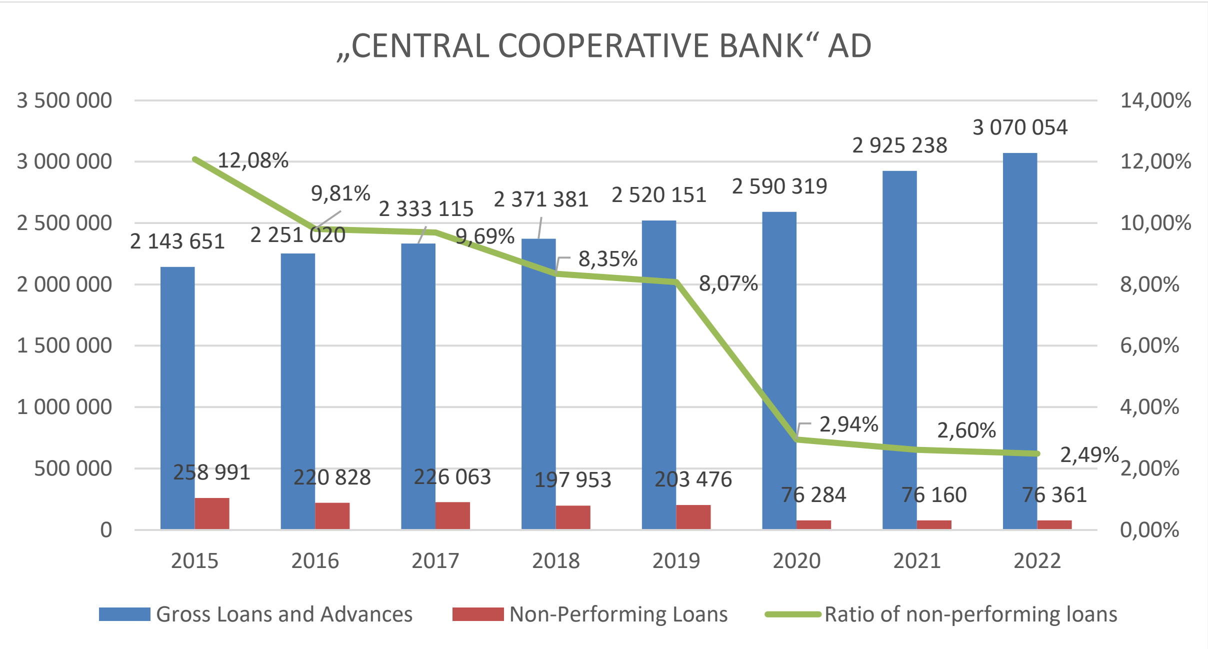
The model shows the following relationships:

- When the FTE number of personnel changes by one percent, the amount of non-performing loans changes by 1.018 percent in the opposite direction, assuming the simultaneous influence of other factors.

- When gross loans and advances change by one percent, the amount of non-performing loans changes by 15.506 percent in the same direction, assuming the simultaneous influence of other factors.
- When performing loans change by one percent, the amount of non-performing loans changes by 15.612 percent in the opposite direction, assuming the simultaneous influence of other factors.
- When the number of branches and offices changes by one percent, the amount of non-performing loans changes by 3.505 percent in the same direction, assuming the simultaneous influence of other factors.

IT expenses are not presented as a separate line item in the annual financial statements of CENTRAL COOPERATIVE BANK for the study period. However, according to publicly available data and information, the Bank has invested in the development of digitization and the implementation of new technologies with the aim of improving its processes. The Bank has successfully implemented many innovative projects. Since data for IT expenses are not available for CENTRAL COOPERATIVE BANK, data are presented instead for the dynamics of non-performing loans relative to the total volume of loans in thousands of BGN for the study period 2015–2022, which is shown graphically in the following figure.

Figure 27. Dynamics of non-performing loans relative to the total volume of loans in thousands of BGN at „CENTRAL COOPERATIVE BANK“ AD for the period 2015–2022.



Source: own calculations based on data from the annual financial statements.

As evident from the presented data, the reviewed period shows a significant decline in both the share and the absolute value of non-performing loans, despite the growth in lending.

Results from the econometric model for assessing the influence of macroeconomic factors in Bulgaria on non-performing loans

Based on the numerous calculations performed using different combinations of factors, the following empirical econometric model with statistically significant influencing factors was identified for assessing the impact of macroeconomic factors on the amount of non-performing loans in Bulgaria for the period 2015-2022:

$$NPL_{SRatio}{}^{macro} = 2.373.UnEmpl_{rt} - 0.394.Salary_{rt} + e_t$$

Of all the factors considered in the theoretical model, only the unemployment rate and the dynamics of the average wage in the country have a statistically significant impact.

The model passes the subsequent tests for heteroscedasticity, absence of autocorrelation, and normal distribution of the residuals.

The model shows the following relationships:

- When the unemployment rate changes by one unit, the ratio of non-performing loans changes by 2.373 units in the same direction, assuming the simultaneous influence of other factors.
- When the average salary changes by one unit, the ratio of non-performing loans changes by 0.394 units in the opposite direction, assuming the simultaneous influence of other factors.

Interrelation between the application of financial technologies and ESG performance - opportunities and challenges for banks

In recent years, ESG criteria have established themselves as an increasingly important factor in assessing the creditworthiness and sustainability of banks. International analysts and regulators emphasize that these criteria significantly influence the credit profile of borrowers and the financial risk undertaken by banks. Academic research concludes that the inclusion of ESG criteria in credit analysis helps identify previously underestimated risk factors. Material ESG issues often play a key role in determining credit quality. In this context, the accelerated adoption of financial technologies in the banking sector provides new tools for enhancing ESG monitoring and analysis. The exploration of the opportunities presented by financial technologies is of essential importance due to their potential to contribute to ESG performance.

The application of financial technologies can contribute to ESG performance in banks through:

1. **Improved management of ESG-related risks** - The application of fintech-based tools enables banks to more accurately forecast ESG-related risks such as environmental impacts or social phenomena. Companies such as McKinsey & Company, Carbon Delta, and others use big data to analyse climate scenarios, collaborating with banks in the process of assessing the financial impact of climate-related risks under various future scenarios.
2. **Improved data management and reporting** - The application of technologies such as AI allows banks to collect and analyse enormous volumes of data, including from various sources, thus helping the institution make more informed decisions regarding sustainability and social responsibility. The tools provided by these technologies can also identify patterns, trends, and anomalies in the performance of ESG reports, leading to more reliable and timely measures.
3. **Engagement of clients and stakeholders with ESG policies** - Banks can offer fintech applications such as robo-advisors that provide personalized ESG guidance to clients based on their individual preferences, thereby promoting sustainable financial practices.
4. **Ethical and Social Impact** - By integrating financial technologies, banks can significantly enhance their ethical and social impact by aligning their operations with ESG principles and contributing to a more sustainable and equitable financial ecosystem. Innovations in technology, such as mobile banking and others, promote access to banking services for underserved population groups.

Through the application of financial technologies and their integration with ESG principles, banks can position themselves as market leaders in sustainable finance. Although financial technologies offer significant potential for improving ESG effectiveness and implementation in the banking sector, incorrect application can lead to the emergence of new challenges. Some of these are related to:

1. **Privacy and data security issues** - The increasing use of big data can heighten the levels of risk associated with data breaches and misuse of customer information, which could undermine the “social” aspect of ESG. To prevent the materialization of this risk,

banks must implement strict cybersecurity measures, conduct regular audits and staff training, and ensure mandatory compliance with data protection regulations such as GDPR.

2. **Negative environmental impact of technologies** - The use of these technologies may also have a negative impact on the environment through high electricity consumption, especially in the case of blockchain technology, which leads to significant carbon emissions. The rapid obsolescence of hardware also generates significant electronic waste, contributing to environmental degradation. To mitigate these effects, banks can switch to renewable energy sources and implement energy-efficient technologies and practices. They can also include programs for recycling electronic waste and reusing outdated equipment.
3. **Digital exclusion** - Relying solely on digital services and channels may exclude certain groups from access to financial services, such as the elderly, low-income individuals, people in rural areas, and those with limited technological literacy. By proactively addressing digital exclusion, banks can align their fintech initiatives with ESG goals, promoting social inclusion and equal access to financial services.
4. **Operational risks** - Relying solely on fintech applications at this stage can lead to operational complexity, which in turn may hinder the effective management and coordination of various systems and processes. To address this, banks need to implement robust risk management policies and ensure continuous process improvement and monitoring.
5. **Greenwashing** - This term refers to misleading claims about the positive environmental impact of a product, service, or corporate activity. Greenwashing in banks can also result from the improper use of fintech tools, such as the use of inappropriate or incorrect data in ESG reporting or excessive reliance on AI-based algorithms without necessary oversight. To avoid this risk, banks must commit to real sustainability practices, ensure transparency in their ESG reporting, and promote a culture of integrity and accountability.

Banks must carefully avoid the materialization of these risks and challenges in order to fully benefit from the opportunities provided by financial technologies in relation to ESG performance.

CONCLUSION

The analysis of the issues addressed in this dissertation provides grounds for drawing the following findings and conclusion:

Conclusions from Chapter One

Chapter One of the dissertation is focused on the theoretical and conceptual framework of credit risk management and financial technologies. The essence of the term "financial technologies" is presented, defining them as innovative technologies and digital solutions that can transform the financial industry. Their goal is to improve and streamline various financial processes and services. In the research, financial technologies in banks are classified into four main groups: Artificial Intelligence, Blockchain, Cloud Computing, and Big Data. This part of the dissertation also explores the stages of credit risk management and traditional practices that are foundational in today's banking but whose application is associated with specific challenges, especially in the context of the modern dynamic and data-rich financial environment. The research conducted in this section leads to the conclusion that relying solely on traditional methods and the lack of implementation of modern financial technologies in credit risk management may result in an ineffective credit policy. Despite the significant progress in credit risk management-from its early stages, when lending was primarily based on personal relationships and trust, to the present, where advanced methods and technologies are used-credit risk remains the most substantial risk faced by credit institutions. Its early identification is essential for effective mitigation. Traditional methods largely depend on historical data and statistical analysis, which may fail to adequately reflect current and future market conditions. Moreover, their application is often accompanied by various challenges, including limited data availability, data quality issues, manual processes that increase the likelihood of human error, the inability to conduct real-time monitoring, and subjectivity in decision-making. These limitations highlight the need for the application of advanced algorithms and intelligent decision-making systems to overcome the existing challenges in credit risk management. Overcoming these challenges will allow banks to more accurately assess a given borrower, which in turn will lead to reduced losses and the maintenance of a competitive advantage. It follows, therefore, that achieving an optimal outcome in credit risk management requires banks to combine traditional practices with modern financial technologies.

Conclusions from Chapter Two

In the second chapter of the dissertation, a detailed examination was conducted on the opportunities and challenges that may arise for banks in the application of financial technologies in the management of their credit risk.

The defined financial technologies in the dissertation can lead to improvements in credit risk management through:

- **Reduction of fraud in loan applications.** The use of artificial intelligence enables the processing of large volumes of data in real time, facilitating the detection of anomalies that may indicate fraudulent activity. In addition, blockchain technology can be utilized for the storage and verification of digital identities, reducing the risk of identity fraud.
- **Automation of processes in credit risk management to increase efficiency.** The application of financial technologies allows for the automation of certain stages of the credit application process, which reduces the risk of human error through the use of predefined rules.
- **Improvement of credit scoring models.** Artificial intelligence algorithms offer innovative tools and methods that allow the analysis of vast amounts of information, including those obtained from non-traditional information channels. At the same time, the use of blockchain technology can consolidate gathered information from different sources—such as credit history, real-time payments, bills, and other financial records—providing a more complete picture of a client's creditworthiness.
- **Improved credit monitoring after disbursement.** Modern financial technologies allow for continuous monitoring of a borrower's creditworthiness. Through this real-time monitoring, banks can identify early warning signs of potential default and take necessary measures to prevent adverse events.
- **Creation of more accurate models for the future behaviour of a borrower.** AI systems and their computational power allow for the creation of detailed customer profiles and predictions of their future behaviour.
- **Improved compliance with regulatory requirements.** Blockchain technology enables banks to enhance their compliance with regulatory requirements by creating a transparent and immutable platform for data management and sharing.

- **Increased transparency and security.** The use of blockchain ensures higher levels of data protection and transparent data governance, which is particularly important for credit institutions.
- **Greater flexibility and scalability.** Cloud computing offers significantly greater scalability and flexibility compared to traditional infrastructure, as it provides the necessary capacity to perform complex simulations that require high computational power.

Despite the advantages offered by modern financial technologies, their application also creates new risks and challenges, requiring banks to take adequate measures to overcome them:

- **Risk of over-reliance on AI-based decision-making algorithms.** Banks should ensure strict control over the algorithms used, requiring prior theoretical validation of their reliability and resilience under various scenarios. It is also important to avoid the use of highly volatile algorithms to prevent incorrect decisions by banks using them.
- **Risk related to data quality and availability.** To minimize this risk, banks should implement a comprehensive data management approach that includes tools for data cleansing and validation, increased data protection levels, integration of more information sources, as well as constant monitoring and regular system updates.
- **Risk related to productivity.** To overcome this risk, banks must ensure continuous training, testing, and validation of their models while guaranteeing their adaptability to changing data, regulatory requirements, and technological innovations.
- **Risk related to integration with existing models.** To successfully overcome this challenge, banks must perform regular system updates and apply a clear, phased integration strategy, ensuring compatibility and minimizing potential risks.
- **Risk related to technological dependency on the service provider.** Addressing this challenge requires diversifying technological sources, developing the bank’s internal technological capabilities, and negotiating flexible contracts with providers.
- **Risk related to cybersecurity.** To effectively manage and mitigate this risk, banks need to implement comprehensive measures including regular information security audits, full data encryption, deployment of advanced anomaly detection systems, systematic staff training to prevent cyberattacks, and strict control over access to information resources.
- **Regulatory and legal challenges.** In many jurisdictions, modern financial technologies and their associated applications are still not covered by a clearly defined regulatory framework. This may raise doubts for credit institutions seeking to use these new technologies.

- **Ethical and social challenges.** The application of modern financial technologies also raises ethical questions related to the collection and use of data from alternative information sources and the extent to which their use is appropriate. Additionally, there are social issues, such as the risk that certain groups of users may be excluded from access to financial services - for example, individuals without access to technology or the skills to use it.

To successfully address the identified risks and challenges arising from the use of financial technologies, banks must implement robust and consistent approaches, clear strategies for regulatory compliance, regular model monitoring, and continuous system updates to ensure transparency and fairness in decision-making. It is important for integration to be phased to reduce the risk of disruption to certain bank processes. With proper preparation, coordination, and aligned decision-making among the various stakeholders involved, these risks can be effectively minimized. The opportunities offered by financial technologies can completely revolutionize credit risk management. The use of these technologies is necessary, as in addition to improving risk management, it will allow banks to better understand their clients and their needs. Banks that manage to leverage the potential of intelligent management systems will have an advantage over others, leading to better market positioning.

Conclusions from Chapter Three

From the research conducted in chapter three, the following conclusions can be drawn:

Among the eight leading banking institutions in Bulgaria that were examined and analysed in detail, the following leading factors were identified as having an impact on non-performing loans:

- In 6 banks – Gross loans and advances;
- In 5 banks – Performing loans;
- In 4 banks – IT expenses;
- In 4 banks – Operating income;
- In 4 banks – FTE number of personnel;
- In 2 banks – Operating expenses, excluding personnel expenses;
- In 2 banks – Personnel expenses;
- In 2 banks – Number of branches and offices.

The first two factors - the gross loans and advances and the amount of those serviced - can be defined as indicators directly related to the amount of non-performing loans.

The other examined variables can be defined as „actual factors“. The leading factor among them is „IT expenses“, which has a significant influence in 4 banks (and possibly more, but the remaining banking institutions did not report these expenses as a separate line item in their financial statements, and thus they could not be included in the econometric models). This was the only indicator not available for all banks, but only for four; however, in each of them, it stood out as a significant factor influencing the amount of their non-performing loans. A consistent trend was observed among these banks—namely, when IT expenses change by a certain percentage, the ratio of non-performing loans changes by a corresponding percentage in the opposite direction, assuming the simultaneous influence of other factors. This leads to the conclusion that IT expenditures have a significant impact on the ratio of non-performing loans. This can be explained as follows: increasing IT spending results in the implementation of modernized technologies aimed at enhancing credit risk assessment mechanisms, automating routine processes, and improving the efficiency of operational management, which in turn contributes to the reduction of non-performing loans. For the remaining banks for which IT expense data is not available, the dynamics of non-performing loans relative to the total loan volume in thousand BGN for the study period 2015–2022 have been graphically presented. From the conducted analyses of publicly available information and interviews with bank employees, it was found that during the research period, banks made significant technological investments and enhancements in their credit risk management processes. As seen in the graphical illustrations, there is a steady downward trend in the share of non-performing loans in these banks compared to the initial period. It is important to note that not only did the share of non-performing loans decrease, but also their absolute value, despite the significant growth in credit activity in the banks during the study period. The absence of specific data on IT expenses in these banks does not exclude the existence of a causal link between technological investments and the dynamics of non-performing loans. This statement is further supported by the interviews conducted with experts and credit risk managers from the studied banks. They also confirmed the conclusion that financial technologies play an increasingly key role in credit risk management. Financial technologies can automate many banking processes, which significantly increases efficiency and reduces operational costs. Artificial Intelligence, when applied in combination with Big Data, can automate tasks such as credit risk assessment, fraud detection, and customer service, saving a significant amount of time and resources. Currently, the most commonly used machine learning algorithms in credit risk assessment among most of the studied banks are logistic regression and decision trees. From the interviews conducted, it becomes clear that investment in these technologies is cost-effective, as their application leads to more accurate risk assessment, process automation, and improved efficiency. The banks note that fintech solutions are thoroughly tested before being implemented.

In this chapter, an econometric model with statistically significant influencing factors was also constructed to assess the impact of macroeconomic factors on the amount of non-performing loans in Bulgaria during the period 2015–2022. This enables banks to evaluate the effect of macroeconomic changes on the share of non-performing loans and thus supports future forecasting. According to the econometric model, the unemployment rate and the dynamics of the average salary in the country have statistically significant influence.

A topic that is becoming increasingly important for banks was also examined—namely, how financial technologies can contribute to the performance of ESG. In recent years, ESG criteria have become an increasingly significant factor in assessing the creditworthiness and sustainability of banks. Material ESG issues often play a key role in determining credit quality. In this context, the accelerated adoption of financial technologies in the banking sector offers new tools for enhancing ESG monitoring and analysis. Advances in technologies such as artificial intelligence, data analytics, blockchain, and cloud computing enable more accurate measurement, reporting, and management of ESG factors. The tools provided by these technologies can also make a substantial contribution to sustainability, thereby supporting responsible and sustainable banking practices.

The results achieved provide grounds to consider that this research has addressed important scientific-theoretical and practical issues, and fully substantiates the defended ***research thesis*** that financial technologies are becoming a significant factor for the successful management of credit risk in commercial banks. Through the integration of modern financial technologies, banks improve their processes, which in turn leads to a reduction in credit risk. The findings of the research fully confirm the ***hypotheses*** formulated in the dissertation that:

- The application of financial technologies enables banks to improve the processes of credit risk management and consequently, reduce non-performing loans.
- Financial technologies have the potential to significantly transform credit risk management in banks through process automation, advanced data analysis and innovative models.

- The improper application of financial technologies poses significant risks to banks, which may lead to an increase in risk levels.

IV. Scientific and applied scientific contributions in the dissertation

The dissertation makes a significant contribution to enriching the existing literature on the impact of financial technologies on credit risk management in banks.

The contributions can be summarized in the following directions:

1. Definition of the concepts „banking fintech“ and „external fintech“ and classification into four main groups of financial technologies
2. Systematization of the stages of credit risk management and identification of existing weaknesses along with opportunities for overcoming them.
3. A comprehensive methodology and models have been developed for assessing the effect of using financial technologies in credit risk management. The methodology has been tested with extensive empirical material, combining statistical data and original empirical research, thereby proving that the use of financial technologies improves the credit risk management of banks.
4. The research experience has been enriched through the development of an innovative method for automated data collection on the application of financial technologies in the surveyed banks, based on web scraping. In this case, the technology simulates human interaction with the website by navigating through its pages and automatically extracting the desired information. The scripts are written in Python.
5. A quantitative and qualitative assessment of the relationship between financial technologies and ESG has been made, and the application of financial technologies for the fulfilment of ESG requirements and sustainable development goals has been evaluated.
6. Successful examples from leading credit institutions around the world regarding the use of modern financial technologies in their credit risk management have been systematized, which can serve as guidance for other institutions seeking ways to apply these technologies and improve their processes.
7. Recommendations have been formulated to assist credit institutions in the application of modern financial technologies in credit risk management.

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