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LARGE LANGUAGE MODELS IN THE BANKING SECTOR: AREAS, OPPORTUNITIES, AND THREATS

DUŻE MODELE JĘZYKOWE W SEKTORZE BANKOWYM: OBSZARY, SZANSE I ZAGROŻENIA

Large language models (LLMs), a rapidly growing area of generative AI (GenAI), are being increasingly applied in banks. The article aims to identify the areas in which banks are using LLMs and to analyse the opportunities and threats associated with their implementation from the perspective of both banking institutions and their customers. The article employs a critical review of the relevant literature and a comparative method. Statistical secondary data from sources such as the Statista database and reports from Accenture, KPMG, PwC, and the European Banking Authority (EBA) support the research. The findings indicate that banks are primarily utilizing LLMs in customer service and internal operations, such as risk management, thereby contributing to their digital transformation. Banks seem to experience more benefits from the implementation of LLMs than their customers. The main challenges identified include legal, ethical, and customer acceptance issues.

Keywords: large language models; LLMs; GenAI; digital banking; banking service automation
JEL: G21, G29

Duże modele językowe (*large language models* [LLMs]) stanowią jedne z najszybciej rozwijających się obszarów generatywnej sztucznej inteligencji (Generative Artifical Intelligence [GenAI]), które znajdują zastosowanie w bankach. Artykuł ma na celu zidentyfikowanie obszarów wykorzystania LLMs przez banki oraz ocenę szans i zagrożeń związanych z wykorzystaniem takich rozwiązań z perspektywy zarówno instytucji bankowych, jak i ich klientów. W artykule wykorzystano krytyczną analizę literatury przedmiotu. Badania poparte są danymi statystycznymi z bazy danych Statista i raportów Accenture, KPMG, PwC oraz Europejskiego Urzędu Nadzoru Bankowego (EBA). Wyniki badań wykazały, że banki stosują LLMs głównie w obsłudze klienta oraz w wewnętrznych operacjach, jak zarządzanie ryzykiem. Wdrażanie LLMs więcej korzyści przynosi bankom niż ich klientom. Największymi wyzwaniami w tym obszarze są kwestie prawne, etyczne oraz akceptacja klientów banków.

Słowa kluczowe: duże modele językowe; LLMs; GenAI; sector bankowy; banki
JEL: G21, G29

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I. INTRODUCTION

Generative Artificial Intelligence (GenAI) is a field of artificial intelligence that includes algorithms capable of creating new content, such as text, images, sounds, code, and videos based on vast amounts of input data (Harrer, 2023). In recent years, language modelling has gained particular importance. Large language models (LLMs) are advanced neural networks that use transformer architecture to enable natural language processing (Leippold, 2023). These models are trained on massive amounts of textual data and often contain billions of parameters. By analysing language patterns, they learn to perform tasks such as writing, translation, and other language-related functions. Due to their capabilities, LLMs are being increasingly adopted across various sectors of the economy, including banking institutions.

This article aims to identify the areas in which banks are using LLMs and to analyse the opportunities and threats associated with their implementation from the perspective of both banking institutions and their clients. Banks play a central role in the financial system. Through their deposit and credit functions, they are not only commercial enterprises aiming to maximize profits but also institutions of public trust. Therefore, the use of AI in their operations can raise significant controversies and questions related to legal, ethical, and customer concerns. It is also important to note that the banking sector is expected to play a pivotal role in the green transformation of the economy (Aracil et al., 2021), as well as in the social sphere (Úbeda et al., 2022). When used properly, AI can be a valuable tool in supporting these efforts.

LLMs, due to their developmental potential, represent an area in need of further research. This article addresses their application in banking activities and makes a significant contribution to the existing body of research. It highlights the potential opportunities and threats from both the perspective of banking institutions and their clients, as customer acceptance is a key factor in the successful implementation of modern technologies in this sector. The research is important not only for digital banks, their customers, and the entire banking sector but also for supervisory institutions. Where possible, the research is supported by statistical secondary data from the Statista database, as well as reports from Accenture, KPMG, PwC, and the EBA.

Section II of the article situates LLMs within the GenAI segment and characterizes their development; section III outlines the research methods. The next section (IV) identifies the areas of banking where LLMs can be applied, and section V analyses the opportunities and threats associated with the use of LLMs in banks, from the perspectives of both banking institutions and their clients.

II. LARGE LANGUAGE MODELS (LLMs) AS AN AREA OF GenAI

GenAI refers to a class of AI models that use neural network algorithms to generate new and original content, such as text, images, or sound by mimicking underlying patterns found in diverse training data (Decardi-Nelson et al., 2024; Feuerriegel et al., 2024). GenAI combines machine learning, natural language processing (NLP), image processing, and computer vision (Lv, 2023).

Large language models such as ChatGPT, Gemini, Claude, Llama (de Silva et al., 2024), and BERT (Dhake et al., 2024; Dong et al., 2024) gained particular popularity with the release of ChatGPT on 30 November 2022, developed by OpenAI (Minaee et al., 2024). This event, described by García-Peñalvo (2023) as a 'black swan', marked a turning point in the development of LLMs. The breakthrough was linked to the fact that it was freely available to anyone interested. As Baidoo-Anu & Ansah (2023) indicated, ChatGPT gained one million subscribers in one week. The next example was Google's 7 February 2023 launch of Bard (renamed Gemini), which competed with ChatGPT (Aydın, 2023; Ram & Verma, 2023). The development of LLMs can be chronologically divided into statistical language models (SLMs), including *n*-gram models, neural language models (NLMs), pre-trained language (PLMs), and large language models (LLMs) (Minaee et al., 2024).

In the development of LLMs, mention should be made of an article published in 2017 under the title 'Attention is all you need' (Vaswani at al., 2017), in which the developers introduced the concept of transformers. Their main components are attention mechanisms, which allow the model to focus on the most important parts of the input sequence. LLMs use neural networks composed of multiple layers, which is why they are categorized under deep learning. They contain billions of parameters, often referred to as artificial neurons, far exceeding the number of neurons in the human brain (Xu & Poo, 2023). The foundation of LLMs involves providing them with sufficiently large sets of textual input data, which can be sourced from various databases, websites, newspapers, scientific articles, and books. Using this data, the model is trained to generate text on any topic, often indistinguishable from the text written by a human (Alghamdi & Alowibdi, 2024).

The transformers on which LLMs are based operate on the encoder-decoder structure. The encoder processes an input sequence, such as natural language, to generate hidden representations, while the decoder uses these representations to produce output, such as translations or text summaries (Feuerriegel et al., 2024). Each layer of this structure contains a multi-headed attention module that learns to assign weights based on the relevance of tokens within the sequences (de Silva et al., 2024). Unlike recurrent neural networks, which process input data sequentially, transformers process entire sequences in parallel. Word embedding also plays a crucial role in LLMs. It involves creating multidimensional vectors that represent words numerically, positioning semantically similar words close to each other in the vector space.

LLMs can be trained using three techniques, which can also be applied to generate content beyond text. These techniques include zero-shot learning, few-shot learning, and fine-tuning. In the zero-shot technique, LLMs generate new content based solely on input, without being trained on specific examples. While this approach is fast and requires no additional data, it is less effective for complex tasks and sentiment analysis, as it may struggle to correctly interpret the intent and content of a statement. Few-shot learning involves teaching the model with a small number of examples, thus allowing it to learn the context and apply this knowledge to specific tasks. While this technique is an improvement over zero-shot learning, its effectiveness depends on the quality of the provided examples. Fine-tuning is a technique by which the model learns from several examples, with parameters updated based on the input. It is useful in adapting the model to perform specialized tasks, whereby it becomes more accurate and reliable. However, it requires a large amount of data, which is often expensive, and the process can also be time-consuming (Sacatani, 2024).

Due to their capabilities in terms of generating realistic content, LLMs have been applied in many sectors and fields (García-Peñalvo & Vázquez-Ingelmo, 2023). An important sphere in which LLMs are increasingly being adopted is the financial sector, most notably banking institutions, which play the most significant role in the financial system. The functioning of banks is very complex, but LLMs can be successfully applied in various departments where textual data and language analysis are required. It should be emphasized that the drive to introduce AI results both from competition with the fintech sector (Rodrigues et al., 2022) and from the growing demands of customers (Kędziera, 2024).

In summary, the development of artificial intelligence is multifaceted, and the different areas are interrelated. One promising area of AI is GenAI, which enables the generation of new content in text, images, and sounds. Within GenAI, LLMs are increasingly being developed and are becoming more capable of generating new textual content, conducting conversations, answering complex questions, and solving problems. Because of their capabilities, they can be used in everyday life and the operation of businesses, including banking institutions.

III. METHODS

Given the theoretical orientation of this study, a critical literature review and comparative analysis were employed. The following research questions were asked:

1. In which banking areas are LLMs used?
2. What opportunities and threats does their use create for banks?
3. What opportunities and threats does their use create for clients?
4. What are the biggest challenges involved in introducing LLMs in banks?

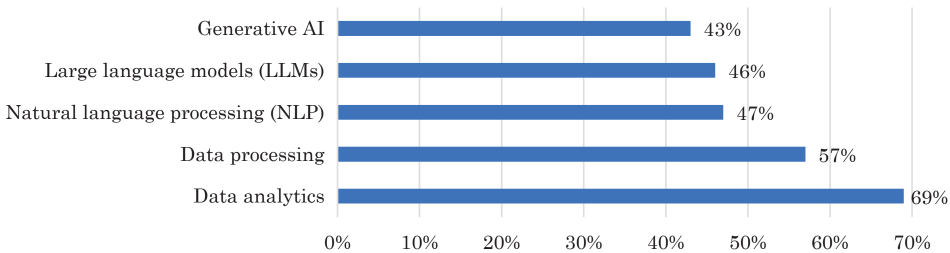
In answering the above questions, both Polish and English scientific and industry publications were used. Then, an analysis was performed on secondary data obtained from the Statista database, as well as from Accenture, KPMG, PwC, and EBA reports. Due to the availability of statistical data, the research period covered the years 2022–2024. The identified areas of LLM application in banks are illustrated with examples drawn from implementations in both Polish and international banks. The added value of the research lies in its summary of the opportunities and threats associated with LLMs from the perspectives of both banks and their clients, as well as the identification of the biggest challenges in this field.

IV. THE SCALE AND AREAS LLM APPLICATION IN BANKS

Finance is the sector with the highest potential to harness GenAI and LLMs for the transformation of its business models. According to Statista, in 2022, only 8% of the world's financial companies considered AI central to their operations, while this percentage is expected to rise to 43% in 2025. This growth will be accompanied by a decline in other categories: the percentage of financial enterprises that indicated widespread adoption, limited adoption, and pilot use is expected to decrease. In contrast, the percentage of financial enterprises that will not use AI will decrease from 6% to 3%. Thus, within a few years, the attitudes of financial institution managers are predicted to change dramatically, indicating the broad possibilities for AI adoption in the financial sector and the competitive pressure being imposed. Figure 1 shows the most popular areas of artificial intelligence (AI) applied to financial services in 2023.

Figure 1

Most popular AI use cases in financial services globally in 2023



Source: Artificial intelligence (AI) in finance, Statista Research Department.

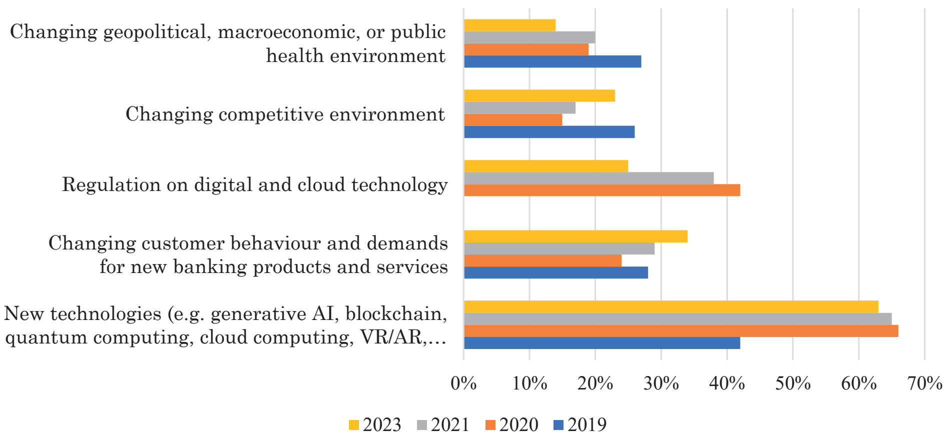
As can be seen from the above data, in 2023, LLMs were used by 46% of entities in the financial services sector; NLP (47%) and general GenAI (43%) were indicated at a similar level. Data analytics (69%) and data processing

(57%) were used most frequently. The financial sector is thus an area where GenAI, including LLMs, has already begun to be implemented on a large scale in various segments of financial services. Moreover, due to its rapid growth, its application is expected to expand further.

The main actors in the financial sector are banks, which, on the one hand, aim to maximize profits and increase profitability (Omankhanlen et al., 2021), and, on the other hand, serve as institutions of public trust (Szustak & Szewczyk, 2021). In this latter role, it is crucial to ensure the safe and responsible use of banking products and services by their customers (Iwanicz-Drozdowska & Nowak, 2024). Modern banking institutions are financial conglomerates combining operations across various financial domains, including banking, insurance, and securities markets (Supangkat et al., 2020). It should be noted that they operate within a constantly evolving regulatory environment, which adds further complexity to their operations. Adapting their business models to evolving conditions requires the integration of new technological solutions that automate multiple areas of their operations (Pawłowska, 2023). Figure 2 shows the main trends affecting the banking sector between 2019 and 2023.

Figure 2

The biggest trends to impact banking according to industry executives between 2019 and 2023



Source: Artificial intelligence (AI) in finance, Statista Research Department.

In recent years, the trend that has had the greatest impact on the banking sector has been the adoption of new technologies. Other important factors include changing customer behaviour and the demand for new banking products and services. Additional factors include technology regulation and cloud technologies, which are reshaping competitive environments. By contrast, changing geopolitical, macroeconomic, and healthcare environments ranked the lowest. It should be noted that this situation changed drastically after the onset of the COVID-19 pandemic. Since 2020, the importance of technology-related trends has increased dramatically. New requirements and shifts in consumer habits have also forced adjustments in service and customer contact.

According to Statista, the areas in which banks have already implemented GenAI solutions include securing payment data (55%) and improved fraud detection (55%), followed by improved credit scoring through synthetic datasets and personalizing the payment experience (47% each). Another area is payment optimization (46%). Other banking segments include improved regulatory compliance and risk management (44%) and authentic chat (43%). Most banks have already introduced various GenAI solutions into their operations, particularly in their payment systems.

Modern banks are increasingly adopting AI solutions, including LLMs, across a wide range of applications, not limited to payment systems. These technologies are being implemented both in internal bank operations and in customer interactions. LLMs can be used in credit processes, trading and portfolio management, financial risk modelling, financial document mining, financial consulting, and customer service (Li et al., 2023).

Banks can use LLMs both in activities that fall strictly within their regulated domain and in areas common to all types of businesses (Szostek et al., 2022). As Klimontowicz (2024) has shown, banks in Poland primarily utilize 'weak' AI solutions. In the front office these solutions are applied mainly in customer service. In the middle office, AI is used for anti-fraud measures, risk monitoring, and compliance. Banks also employ AI in marketing and human resources management. In the back office, the primary area of application is risk management, particularly credit risk. Some of these areas, such as customer service, are already well-developed, while others, like risk management, remain in the development phase (Iwanicz-Drozdowska et al., 2023).

The main area is customer service (Accenture, 2024; Kędziera, 2024; Klimontowicz, 2024). For example, ChatGPT can be used in various segments such as customer service, content creation, and as a personal assistant (Ram & Verma, 2023). Because of their ability to process language, the most popular are chatbots, voicebots, and virtual assistants (Umamaheswari et al., 2023), which have direct contact with the customer.

LLM usage in customer service increased from 25% to 60% in 2023–2024 (Nvidia, 2025). In Poland, PKO BP (2025) bank, the leader of the banking sector, offers its customers as many as 17 voicebots and to provide customer service on the hotline, remind customers about outstanding payments, conduct surveys, research product purchase tendencies, and protect customers' finances. Another example is Alior Bank (2023), which since 2021 has used the InfoNina bot as well as a platform for automatic conversation analysis ('Speech'), thanks to which employees can easily categorize conversations and control their quality. Nest Bank (2025) provides a GPT-4-based voicebot called N!Aystsent to selected users of its banking application, which executes various commands and understands informal language. In the UK, the British bank NatWest plans to use OpenAI technology to enhance the capabilities of its customer service chatbot Cora and employee virtual assistant AskArchie (Cruise, 2025).

An important area of LLM application in banks is customer satisfaction research. Instruments using LLMs can conduct a conversation with customers using surveys and follow-up questions. Complaint handling and sentiment analysis are also important in this context, as they provide insights supporting the introduction of new financial products and services.

Another major application is fraud detection. By mapping and analysing the complex web of relationships between entities, Graph LLMs can identify hidden patterns that indicate fraud. For example, they can detect collusion between seemingly unrelated accounts or policies, signalling threats that linear models miss. This solution was implemented by BNP Paribas (PwC, 2024). Artificial intelligence can provide more efficient detection of suspicious transactions, thereby reducing the risk of money laundering. Moreover, AI can detect the risk of cyberattacks by formulating various scenarios and preparing response plans, which may translate into increased security (Accenture, 2024).

Within the compliance space, Graph LLMs can automate the complex tasks of regulatory compliance research by understanding regulatory requirements in the context of the organization's entire data ecosystem. They can flag potential compliance issues in real time and streamline reporting processes (PwC, 2024).

Another issue is the advertising and marketing of banking products and services in which LLMs can be used; for example, in formulating advertising slogans based on keywords and, using other tools within the general GenAI, creating advertisements by generating images, videos, and sound. An example is the first application in Poland of the ING bank (2023), *Me in the future powered by AI*, used to visualize one's life in retirement. To activate, users had to finish the sentence 'In the future I will...' and send their photo. AI models (Midjourney, DALL-E, Stable Diffusion's Image-2-Image, and Topaz) were combined individually. As the bank representatives indicated, this campaign, which ran from 9 January to 5 March 2023, increased sales of ING Bank Śląski pension products. In turn, Santander Consumer Bank (2023) developed an advertising campaign *Communication created with AI* to increase loan sales.

The next area is human resources management. One such area is employee recruitment. The use of LLMs may enable the drafting of requirements for individual positions and the formulation of advertisements, followed by the selection of documents submitted by potential candidates, or even conducting the first stages of interviews and inviting them to the actual interview. LLMs can also search for people with appropriate qualifications on portals such as LinkedIn and select them. After employment, they can introduce a new employee to work.

Furthermore, AI can be used in the process of motivating employees. An example is a solution implemented by PKO BP, which uses an image recognition algorithm to analyse the employee's facial expressions. Artificial intelligence from PKO BP, developed by the start-up Quantum CX, counts how often the employee smiles during a conversation with a customer, so that the most friendly employees have a chance to win motivational rewards (Newsroom BrandsIT, 2019).

Another area is employee training, which is related to education. LLMs can help select lecture content, methods of presenting it, and formulate knowledge tests. LLMs can be virtual trainers and develop learning platforms for current employees and new hires.

LLMs are also becoming increasingly important in playing a therapeutic role. In this case, an example would be the HereAfter AI application, which allows the memory of the deceased – their appearance and voice – to be retained in virtual conversations after death. In the case of banks, applications may also include supporting employees in difficult moments of professional and everyday life or consoling them. They can also integrate employees and resolve their conflicts, as a real therapist would.

Risk management, including credit risk, is another area in which AI is used in banks. In this field the application of LLMs may extend beyond the indicated areas of banking operation. JPMorgan Chase Bank has launched an AI tool called LLM Suite for 60,000 employees. The solution supports document summarization, translation and text generation, integrating with everyday work processes (Kessel, 2024). The implementation of LLMs in the credit process is also visible. An example is the solution of UBS bank, which launched a pilot programme of instant credit for small and medium-sized companies. It uses AI to speed up the decision-making process, bypassing traditional credit analysts (Reuters, 2024). HSBC AI Markets launched a digital services offering that uses purpose-built natural language processing (NLP) to enrich the way institutional investors interact with global markets. In due course, it will also be made available to large corporations.

Moreover, LLMs can be useful in spreading the concept of sustainable development. They can create training platforms for economic, financial, social, and environmental education, which, from a social aspect, can constitute charitable support for those in need and serve social inclusion. In this area, LLMs are also able to invent new financial products and services related to the Sustainable Development Goals, as well as provide support within non-financial reporting. Their support in identifying solutions related to, for example, saving energy, water, or paper is also important. As it turns out, this area is the least exploited when it comes to implementing LLMs. In 2024, in the European banking sector, only 1.18% of respondents indicated that they use AI in carbon footprint estimation, 15.28% use GenAI, and as many as 83.53% did not use this type of solution at all (EBA, 2025).

It is important to educate not only employees but also clients and society as a whole. In this area, LLMs can help plan and implement educational campaigns in finance, which may promote financial inclusion. They can also serve as a support centre for customers who are, for example, in a difficult financial situation.

To sum up, the finance sector, including banking institutions, is increasingly implementing LLM solutions on a broad scale. The primary area of application is customer service. Additionally, LLMs are being used in fraud detection, compliance, risk management, advertising and marketing of banking services, as well as in human resources. An important area with strong potential for future development is the use of LLMs in advancing sustainable development initiatives. They can support sustainability efforts through enhanced reporting, carbon footprint calculation, and the implementation of related solutions.

V. THE OPPORTUNITIES AND THREATS OF LLMs FROM THE PERSPECTIVE OF BANKING INSTITUTIONS AND THEIR CUSTOMERS

As the research of Iwanicz-Drozdowska et al. (2023) shows, the implementation of new technologies in the banking sector aims to meet customer needs while enhancing the productivity and efficiency of internal processes. Risk management remains an area requiring further development. These technological advancements present both opportunities and risks that must be carefully analysed from the perspectives of both banks and their customers (Grzywacz & Jagodzińska-Komar, 2021). The use of LLMs in banking offers numerous benefits and presents an opportunity to drive innovation, potentially boosting the competitiveness of banking institutions by expanding their customer base, increasing profits and gaining market share.

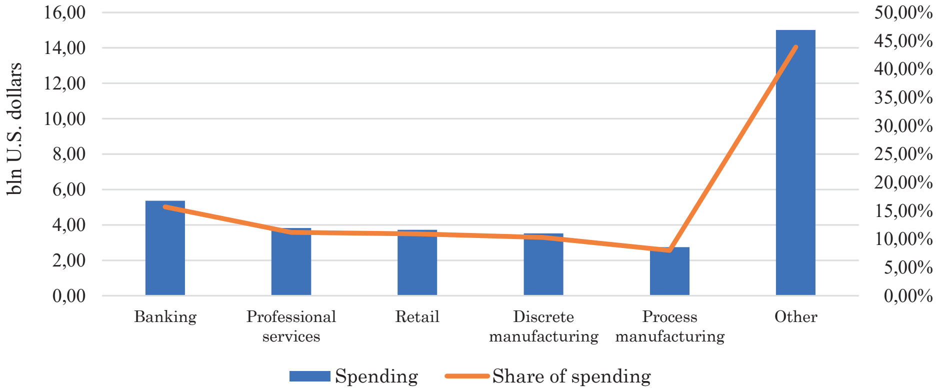
The development of digital banking generates technological, operational, economic, and social impacts. A key motivation for introducing GenAI, including LLMs – beyond competing with fintechs – is to enhance productivity and, ultimately, increase financial profits. According to Accenture (2023), the potential productivity increase due to using GenAI solutions ranges from USD1.3 to 1.9 trillion, or 5% to 8% of GDP, in the United States alone. In financial services, the potential productivity increase is estimated at USD103 billion to USD158 billion. Banking is likely to see a more significant impact from AI than any other industry: banks are expected to increase their productivity by approximately 22–30% for this reason (Accenture, 2024).

However, it is necessary to incur expenditure on investments related to the purchase of new technological solutions. The estimated expenditure on investments in AI in banks compared to other sectors is presented in Figure 3.

In 2023, the estimated spending on AI systems in Europe amounted to approximately USD34 billion. The largest share among the mentioned sectors was allocated to banking, at about USD5 billion, which constituted approximately 16% of the total. Other sectors included professional services (USD3.8 billion; 11.2%), trade (USD3.7 billion; 10.9%), discrete manufacturing (USD3.5 billion; 10.3%) and the manufacturing sector (USD2.7 billion; 8%). As already mentioned, investments in GenAI are intended to generate additional revenues and profits and, as a result, improve the bank's profitability. Figure 4 shows their potential impact on the revenues of various sectors.

Figure 3

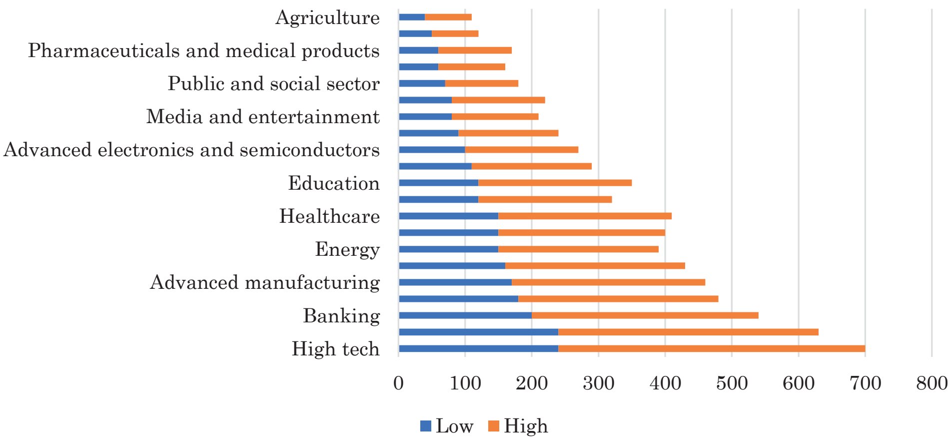
Estimated spending on artificial intelligence (AI)-centric systems in Europe in 2023, by industry (USD billion and share)



Source: Artificial intelligence (AI) in Singapore, Statista Research Department.

Figure 4

Potential impact of generative AI on industry revenues 2023, by industry



Source: Artificial intelligence (AI) in Singapore, Statista Research Department.

The high-tech sector was the sector whose revenues were most influenced by the use of GenAI. The banking sector came second, followed by advanced manufacturing. The sectors whose revenues were least impacted by GenAI were agriculture, pharmaceuticals and medical products, and the public and social sectors. The banking sector is among those expected to experience the most significant benefits in the form of increased revenues. However, it is also one of those that most recognize the potential of GenAI and incurs some of the most significant investment expenditures in this area. Apart from the financial benefits, there are other potential opportunities and threats related to introducing GenAI and LLMs for banks and their customers.

The primary benefits of implementing broadly defined AI solutions include increased productivity, revenue, profits, and profitability. According to Accenture (2024) estimates, bank revenues could rise by 6% or more within three years. The growth can be driven by cost reductions achieved through the virtualization of customer service, workforce optimization, and reallocating employees to other departments. As Flejterski (2024) has noted, further cost savings are possible through the automation of routine processes such as accounting, settlements, transaction verification, and financial data analysis. These improvements contribute to time and resource savings, enhanced risk management, and more efficient resource utilization. Particularly impacted are time-consuming and repetitive tasks that demand high levels of employee concentration and are prone to human error (Dziedzic, 2022). It is important to emphasize that while cost reductions tend to be realized in the long term, the initial implementation of AI involves significant upfront expenses, which should be viewed as strategic investments.

One of the concerns reported by bank employees is the fear of job loss. However, it has been pointed out that the use of AI leads to time savings and reduced customer service costs. In terms of employees, AI helps reduce their workload while increasing efficiency. As noted by Waliszewski and Warchlewska (2020), in the context of the development of robo-advisory, the most likely model in the near future will be a hybrid one, where traditional advisors use modern technologies and robo-advisory tools to assist them in their work with customers. Despite its advancements, AI still requires human oversight and continuous data updates.

AI can also help create personalized offers for customers, including the introduction of innovative banking products, easier account management, and improved banking applications. Additionally, it enables faster feedback from customers regarding service quality and complaints. Using the example of robo-advisors, it was found that their advantage over human advisors lies in lower costs (Waliszewski & Warchlewska, 2020). AI enhances a bank's innovativeness, helping it gain a competitive advantage, which is crucial in the context of competition from other financial institutions (Kędziera, 2024).

One of the identified threats is the need to ensure the protection of customers' personal data, which also entails the risk of system errors and the requirement for AI systems to comply with legal regulations (Flejterski, 2024). Another concern is the risk of low customer loyalty. Customers are often not strongly attached to a specific bank brand and tend to use services from multiple banks simultaneously (Accenture, 2024). The loss of direct contact and a personalized approach, devoid of human emotions and empathy, may lead to customer dissatisfaction and potentially cause the bank to lose customers due to inadequate service, lacking emotional engagement. Bank customers experience the greatest opportunities and threats in customer service and the credit process, as these areas affect them directly. Customers typically do not notice improvements in internal banking operations. Therefore, the primary benefits are related to tools such as various bots acting as advisors. In this regard, it is worth highlighting the ability to quickly obtain answers to questions 24/7, such as inquiries about account balances or transactions, without the need to visit a bank branch or interact with an employee (Cimpeanu et al., 2023). Another benefit is the use of virtual assistants to help manage personal budgets, especially for optimizing expenses.

However, LLMs do not fully understand human language (Harrer, 2023; Kibriya et al., 2024). They may struggle with different accents, dialects, or when the customer is a foreigner, and they may misinterpret numbers, leading to misunderstandings and customer dissatisfaction. Another risk is the potential for AI 'hallucinations', where false information is provided, misleading either employees or customers. Additionally, chatbots, voicebots, or virtual assistants lack the ability to empathize with the customer's situation, which can result in the loss of a personalized approach when addressing financial issues and create discomfort due to a lack of empathy. There is also a greater risk of hacking attacks that could bypass voice analysis and other security measures, facilitate phishing attempts, and lead to the creation of more complex and elusive viruses (Accenture, 2024). Bots, being focused primarily on resolving typical problems, may fail to address the more complex issues that customers face. A major disadvantage of robo-advisors is the absence of direct human interaction, and the solutions they provide may not be fully tailored to an investor's unique situation and risk profile, as the surveys they complete often fail to capture the client's overall financial context (Waliszewski & Warchlewska, 2020).

The key opportunities and threats associated with the implementation of GenAI and LLMs in the banking sector are summarized in Table 1.

It appears that banks benefit more from using LLMs than customers, primarily due to the many areas in which banks can implement these solutions. For customers, however, the solutions implemented within internal operations remain invisible, and they primarily benefit from improvements in customer service and the range of products and services offered. The greatest threat to the implementation of new technologies in the banking sector is the unclear legal situation (Staegemann et al., 2025). Regulations in this area should be designed to protect customers without hindering the development of AI (Waliszewski, 2020). Achieving both of these objectives simultaneously is a challenging task (Ślażyńska-Kluczek, 2021). One specific area where this challenge is evident is the assessment of creditworthiness and credit risk, which remains a strictly banking activity.

Kowalski (2024) highlights the legal risks associated with digital banking, referencing the AI Act,[1] which came into effect on 12 July 2024. Its application

[1] Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence and amending Regulations (EC)

is being introduced in stages, and the Act categorizes AI risks into four levels: unacceptable, high, limited, and minimal. Ensuring transparency and clarity of GenAI is also crucial – meeting the standards related to these principles is a condition for their application.

Table 1

Opportunities and threats of implementing GenAI and LLMs in the banking sector

Opportunities	**Threats**
Banks' perspective	
– time and resource savings through automation of banking operations – opportunity to increase revenues, profits, profitability, competitive advantage and market share by increasing the level of customer satisfaction – increased innovation	– high implementation costs – need for human supervision and data updates in models – risk of limited acceptance by customers – legal and ethical risk, personal data protection – risk of failures and hallucinations – risk of loss of trust from society
Customers' perspective	
– personalized financial advice – shortened formalities – better customer service – constant control over funds	– receiving incorrect answers – lack of transparency and understanding of algorithms – loss of human contact

Source: the author's own elaboration.

A new legal aspect that has emerged is civil liability for damages caused by AI. Traditional approaches to liability are proving insufficient in the context of AI. A significant problem arises not only from the lack of appropriate legal solutions within individual countries but also from the cross-border operations of banks. This issue is further explored in the article by Szpyt (2024). Since AI does not have legal personality, it cannot make decisions for employees or be held accountable, raising the question of who should be held responsible for any mistakes made (Dziedzic, 2022).

In the legal context, new risks can be expected, and their regulation will likely take years. It is important to note that, while these regulations will enhance the safety of bank operations and their accountability to customers, as Nowakowski and Waliszewski (2022) point out, the banking sector is already heavily regulated, and these new rules will impose additional obligations, costs, and complexities.

Another threat that is difficult to eliminate but requires increased attention from supervisory authorities is AI-related ethics. This is particularly relevant for banks, which are trusted public institutions that handle sensitive

No 300/2008, (EU) No 167/2013, (EU) No 168/2013, (EU) 2018/858, (EU) 2018/1139 and (EU) 2019/2144 and Directives 2014/90/EU, (EU) 2016/797 and (EU) 2020/1828 (Artificial Intelligence Act).

data and adhere to the principles of banking secrecy. Ethical considerations, such as transparency in dealings with customers, non-discrimination, and the protection of personal data, are crucial. This is especially important in the credit process, where various personal data are processed. It is essential to inform customers about how their data are processed and the stages of decision-making, particularly in the case of negative credit decisions.

Within the framework of ethics, it is important to establish various standards, which should be created by industry institutions, professional organizations, internal bodies of financial institutions, and supervisory authorities (Nowakowski & Waliszewski, 2022). Scoring systems can lead to discrimination and unfair assessments of individuals due to the lack of standardized methodologies and transparent procedures. Additionally, the automatic identification of individuals could be misused to track citizens (Grzywacz & Jagodzińska-Komar, 2021).

An intriguing issue is the potential use of social media data during the credit process. In Poland, this is prohibited, as outlined in Article 105a, Sections 1 and 4 of the Banking Law Act.[2] However, such practices are allowed in China, where the Social Credit Scoring system rates citizens based on their social and digital behaviour, often with the use of AI (Pajor, 2024).

Violating legal and ethical principles can have negative consequences, leading to a loss of trust in banking institutions. This, in turn, can harm the reputation that banks have worked hard to rebuild since the global financial crisis. Rebuilding such trust may prove difficult. It should also be emphasized that the risk extends to the entire banking sector and to the supervisory bodies responsible for security. The introduction of AI solutions in banks increases the exposure of the entire sector to technological risks, cyberattacks (Choithani et al., 2024), and the potential erosion of societal trust.

The identified areas represent potential opportunities and threats for the use of LLMs in banking institutions, both for banks and their customers. It should be noted that temporary threats can evolve into opportunities, provided that employees use LLMs correctly and continue to enhance their skills. Supervision plays a critical role in this regard. These technologies are still developing and cannot operate independently without human oversight. Customer acceptance is also crucial, which is why LLMs must closely resemble human interactions, particularly in customer service.

According to survey research by Jambulingam et al. (2023), most bank customers in Malaysia aged 21–32 used chatbots, voicebots, and applications to conduct banking transactions. The main reasons for this were time saving, convenience, multitasking, and ease of use. Some also viewed the use of these technologies as enjoyable. However, the reasons for the lack of adoption of such solutions by some bank customers are equally important. These include concerns about insecurity, risk, and uncertainty, as well as fears that the system may misinterpret the customer's voice, leading to an increased risk of

[2] Banking Law Act, 29 August 1997, Journal of Laws of the Republic of Poland 1997, No. 140, item 939 as amended.

scams. As a result, not all bank customers accept LLM-based solutions offered by banks, but many view them with curiosity and use them on a trial basis.

The adoption approach may vary based on factors such as customer age, wealth level, lifestyle, attitude towards innovation, trust in banking institutions, and the economic development and financial systems in which they operate. Nonetheless, customer opinion is a decisive factor in the success of LLM implementation, indicating a need for further research in this area.

Another example is the research conducted on Nigerian bank customers using chatbots. The results showed that factors such as trust in the platform, security of financial transactions, user interface quality, chatbot response speed, and the ability to meet customer needs were crucial for users (Mogaji et al., 2021).

Additionally, research conducted by Warchlewska and Waliszewski (2020) in Poland explored the acceptance of robo-advisors in investment advice. The study revealed that the perception of robo-advisors as ethical and customer satisfaction influenced the likelihood of recommending them to others. Furthermore, individuals using a balanced investment strategy were more likely to adopt robo-advisory services. Older individuals and those with higher education were also more inclined to invest in robo-advisory services. A longer period of using robo-advisors was associated with larger amounts of assets entrusted to the service.

Research conducted by Waliszewski (2022) in Poland and Slovakia found that the COVID-19 pandemic did not negatively impact the personal finances of users of robo-advisory services. However, Polish and Slovak users differed in their investment methods during the pandemic and their plans post-pandemic. Many used spreadsheets and specialized banking or non-banking applications to manage their personal finances.

In summary, the use of LLMs in banks presents both opportunities and threats. The primary opportunity for banks is the potential to increase revenues, profits, and market share by enhancing competitiveness. However, this opportunity comes with the threat of high investment costs. Other opportunities for banks include accelerating internal operations, such as document examination and the credit process, by supporting or replacing employees. Additionally, LLMs can improve risk management by detecting suspicious transactions more efficiently. There is also the potential to unlock the innovative capabilities of employees by freeing them from routine tasks and offering further training opportunities. Moreover, LLMs may contribute to sustainable development by supporting non-financial reporting and promoting knowledge in this area. These solutions may also reduce costs, such as paper consumption (Noreen et al., 2023).

On the other hand, threats may include a lack of customer acceptance, ethical and legal issues related to copyright, and potential limitations on the use of LLMs in this context. For customers, the opportunities lie in the faster access to bank products and services, better management of account funds, and the ability to receive personalized offers. However, the threats remain: lack of trust in LLMs solutions, concerns over empathy, and worries about the security of funds and the confidentiality of data.

VI. CONCLUSIONS

LLMs have applications across many industries, including finance and banking institutions. Banks are utilizing LLMs extensively in both internal operations and customer service, as well as consulting and customer satisfaction surveys. The primary application is in customer service. Additionally, LLMs are being used for fraud detection, compliance, risk management, marketing and advertising of banking services, and employee management. A significant area that may develop in the future is the use of LLMs in advancing the concept of sustainable development.

Within banks, these areas include document analysis, risk management, credit process analysis, and compliance with legal regulations. Externally, LLMs contribute to customer service, consulting, and customer satisfaction surveys. In the future, LLMs may also play an important role in employee recruitment and training, therapy, support, and conflict resolution. Another area is advertising banking products and services. Therefore, LLMs are being applied across various aspects of banking operations and may eventually extend into areas not yet fully realized, such as supporting sustainable development.

In the front office, the focus is on customer service. In the middle office, banks are applying AI for anti-fraud risk monitoring and compliance, marketing, and human resource management. In the back office, risk management, especially credit risk, remains the primary focus.

These solutions present specific opportunities and threats from both the perspective of banks and their customers. For banks, the primary opportunities include the high potential for increased productivity, unlocking employees' innovative potential, expanding the customer base, enhancing market position, and improving profitability. However, these benefits come with significant risks, such as the high costs associated with investing in new technologies, potential fraud, and the risk of technology failures. From the customer perspective, the main opportunities and threats are linked to the virtual transformation of customer service. While services may become faster and more efficient, a lack of empathy could result in customer dissatisfaction and potential loss. Therefore, banks stand to gain more opportunities from these technologies, provided they are properly developed and managed. It is crucial to emphasize that these solutions are still evolving and must be supervised by specialists.

The greatest challenges for LLMs in banks are legal and ethical issues, which require continued work from various institutions to regulate and ensure the security of these technologies. Additionally, the acceptance of these solutions by bank customers is another crucial condition for their success. If used appropriately, LLMs can contribute significantly to the role of banks in supporting a sustainable economy.

As this field remains in its early stages, many research challenges persist. One key area for future research is finding ways to mitigate the risks associated with LLMs in banking operations, thereby increasing security and avoiding legal and ethical pitfalls. Another area to explore is examining customer acceptance, through surveys and interviews, as well as analysing the experiences of customers who have already used such services. In this regard, it is important to consider various customer segments and measure their satisfaction and willingness to adopt this type of solution. This will contribute to maintaining ethical relations with bank customers. Success in the development of digital banking will require close coordination between legal experts and those implementing AI technology due to the lack of clear regulations regarding LLM implementation, copyright issues, and the risk of lawsuits.

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