INTELIGENȚA INVESTIȚIILOR DEZLĂNȚUITĂ: STRATEGII FINANCIARE DE AFACERI PRIN INTERMEDIUL LLM-urilor

Investment intelligence unleashed: business financial strategies through LLMs

Tirnacop Bianca Alexandra
alexandrabianca127@gmail.com

Coordonatorul lucrării
Prof. univ.dr. Șchiopu Andreea Fortuna

Rezumat: Acest articol explorează impactul FinTech, al inteligenței artificiale (AI) și al modelelor lingvistice de mari dimensiuni (LLM) asupra sectorului financiar. Acesta examinează ascensiunea perturbatorilor FinTech și utilizarea de către aceștia a tehnologiilor de ultimă oră, precum AI și LLMs, în vederea contestării paradigmelor bancare tradiționale. Studiul investighează implicațiile acestor inovații asupra accesului consumatorilor la serviciile financiare, a mediului concurențial și a reglementărilor. Din punct de vedere metodologic, acesta utilizează analiza literaturii de pentru a sintetiza cercetările existente și datele empirice pe această temă. Principalele constatări relevă o schimbare semnificativă în dinamică pieței, companiile FinTech câștigând teren în domeniul serviciilor de creditare și de plată, în timp ce băncile tradiționale se confruntă cu provocări în adaptarea la această perturbare digitală. În plus, studiul evidențiază potențialul LLM-urilor în ceea ce privește automatizarea sarcinilor și furnizarea de informații financiare personalizate, alături de preocupări precum luarea de decizii părtinitoare și riscurile legate de confidențialitatea datelor. Prin adaptarea reglementărilor și măsuri solide de securitate cibernetică, articolul pledează pentru o inovare responsabilă pentru a asigura un viitor financiar sustenabil și incluziv. Această cercetare subliniază importanța colaborării și a perfecționării continue a tehnologiilor pentru a naviga în mod eficient în domeniul financiar.

Cuvinte cheie: Fintech; LLM; Trading; Afacere; ROI

Abstract: This article explores the transformative impact of FinTech, Artificial Intelligence (AI), and Large Language Models (LLMs) on the financial sector. It examines the rise of FinTech disruptors and their utilization of cutting-edge technologies like AI and LLMs to challenge traditional banking paradigms. The study investigates the implications of these innovations on consumer access to financial services, the competitive landscape, and regulatory frameworks. Methodologically, it employs a literature review approach to synthesize existing research and empirical data on the subject. Key findings reveal a significant shift in market dynamics, with FinTech companies gaining momentum in lending and payment services while traditional banks face challenges in adapting to this digital disruption. Additionally, the study highlights the potential of LLMs in automating tasks and providing personalized financial insights, alongside concerns such as biased decision-making and data privacy risks. Through regulatory adaptation and robust cybersecurity measures, the article advocates for responsible innovation to ensure a sustainable and inclusive financial future. Overall, this research underscores the importance of collaboration and continuous refinement of technologies to navigate the evolving financial landscape effectively.

Keywords: Fintech; LLM; Trading; Business; ROI

Clasificare JEL: M2

Clasificare REL: 11A, 11Z

1. Introduction

Industry 4.0, which represents the rapid growth of technology, is transforming several industries, but none more so than finance. Large Language Models (LLMs), FinTech, and AI are all contributing to a significant revolution of the financial industry. Innovative FinTech disruptors using state-of-the-art technologies to deliver seamless and customer-focused financial services are challenging established banking structures. This introduction lays the groundwork for understanding the ways in which technology and finance interact dynamically as it explores the goals, approaches, and most important discoveries of this research. This research attempts to clarify the effects of technological breakthroughs on consumer access, market dynamics, regulatory frameworks, and the general sustainability of the financial ecosystem through a review of the literature and empirical data. This study aims to further the awareness of the changing financial landscape and the need for responsible innovation in the digital age by exploring the revolutionary possibilities of FinTech, AI, and LLMs, along with the risks and regulatory issues that come with them.

2. Literature Review

In this section we analyse and interpret findings from a comprehensive list of specialty materials regarding financial technologies, large language models and how the two are interrelated. The first two subchapters are for warm up, the rest are a dive in.

2.1 Introduction to Fintech

According to Popkova et al (2021), Industry 4.0, which emerged with the Fourth Industrial Revolution, is a fast expanding landscape that includes advanced financial technology, or FinTech. Modern FinTech operations include a range of examples of intelligent investment decision support. These include things like bank credit scoring, AI-powered brokerage apps, digital investment platforms, chatbots for financial institutions, smart assistants, and the use of smart technology to improve financial security (Kazachenok et al, 2023:p.2). FinTech refers to automated internet services that employ computer algorithms to manage investment portfolios and offer financial advice (Agnew, Mitchell, 2019: p. 2). As we go further into the Fintech disruption, we uncover a new frontier brimming with possibilities and problems that is revolutionizing the banking industry right before our eyes. Mobile technology has played a significant role in driving the adoption of Fintech and has empowered consumers to access financial services conveniently, regardless of time or location (Negi, 2023: p. e770).

The financial realm is experiencing significant transformations propelled by the relentless advancement of technology. The traditional banking industry has undergone tremendous transformation as a result of the financial technology (Fintech) businesses' quick rise to prominence and rapid development. Fintech disruptors have utilized cutting-edge technologies such as blockchain, artificial intelligence, and mobile applications to provide seamless, effective, and customer-centric financial services, thereby challenging the traditional banking paradigm. Consequently, traditional banks must adjust to this evolving environment or face the threat of becoming outdated (Negi, 2023: p. e769). Consumers are currently benefiting from improved access to financial services, tailored experiences, and the potential to reduce payments. Nevertheless, they grapple with apprehensions regarding data security, privacy issues, and the possibility of excluding marginalized populations from the digital economic transformation (Negi, 2023: p. e770).

In accordance with findings from IBM's investigation in 2016, it was determined that approximately 90% of global data originated within the timeframe spanning from approximately 2014 to 2016 (Loechner, 2016). This surge in data creation presents distinct challenges (Arvind, Heinz, 2021: pp. 212-213). Shareholders, investors, and specialised financial institutions own the majority of the available financial assets and are in charge of making important investment decisions. There is a tendency for the risks to rise when these decision-makers give priority to economic concerns. The payback period, return on investment, and an investment project's effectiveness in comparison to alternatives are all examples of economic considerations (Kazachenok et al, 2023: p. 2). LLMs can drive sophisticated chatbots that can comprehend client inquiries and offer tailored answers. LLM-driven chatbots improve customer experience by doing tasks including interpreting financial jargon, addressing transaction errors, and monitoring account balances (Akyurek, 2023).

The Fintech crash resulted in a reduction of banks' market share in the lending sector to 70%, with Fintech companies seizing 30% of the market. This shift indicates that Fintech companies have garnered momentum within the lending sector, posing substantial competition for traditional banks. For payment services, traditional banks have similarly experienced a notable decline in market share, plummeting from 90% pre-Fintech disruption to 60%. Fintech firms now hold 40%. These figures underscore Fintech's disruptive impact on the payments landscape, resulting in a redistribution of market dominance. In the asset management sector, traditional banks have maintained 95% market share compared to their pre-Fintech levels. However, their market share has decreased to 80% in the wake of an 8-year Fintech disruption, with Fintech companies now holding a 20% share of the market. While traditional banks still dominate the sector, these figures indicate that Fintech firms are increasingly providing alternative wealth management solutions (Negi, 2023: p. e772).

AI is used in insurance for damage assessments, analyzing images and videos to estimate repair costs, reducing physical inspections and expediting claims processes. Artificial intelligence (AI) will be used more in credit choices, determining a person's eligibility for a loan based on credit scoring and, consequently, in lending recommendations. The shift towards hyper-personalization in banking products, driven by AI, raises concerns about the potential marginalization and exclusion of demographics deemed less profitable, exacerbating issues of financial exclusion. While pricing discrimination based on risk is common, hyper-personalization takes it further, tailoring pricing to individuals rather than groups. Historically, market incentives, not moral obligations, have driven banking inclusivity, but AI's ability to assess an individual's potential value may alter this dynamic. AI's predictive capabilities could forecast an individual's profitability, product consumption patterns, and potential costs for a bank, potentially reshaping banking practices (ICAEW Insights, 2023).

2.2 Introduction to LLMs

Bengio Y., Ducharme R. and Vincent P. describe language model as a statistical framework that undergoes training using vast text datasets to forecast the likelihood of word sequences occurring together (Li et al, 2023: p.1). Almutiri T. and Nadeem F. claim that this probability is broken down into conditional probabilities of each word given its preceding words. Language model architectures have evolved over time, starting with n-gram models that treated word sequences as Markov processes (Li et al, 2023: p.1). It is significant to note that the creation of novel neural network topologies, the availability of large-scale datasets, and advances in computational capacity have been the primary forces behind the growth of language models. These models' greatly improved language production and interpretation capabilities allow for applications in a variety of fields and industries (Li et al, 2023: p. 2). Large Language Models (LLMs) have advanced quickly in recent years, changing the face of many different industries, including finance (Akyurek, 2023).

According to Gavrilova et al (2018), AI is utilised everywhere. Recent studies demonstrate the significance of artificial intelligence and its enormous effects on the financial markets (Tokic, 2018), where a variety of issues can be resolved through the application of machine learning techniques. Pattern detection, risk analysis, investment profile analysis, portfolio development, decision support, and forecasting are a few examples (Vella & Ng, 2015)(Petrelli, Cesarini, 2021: p. 247). As widely agreed, AI, described as the capacity of computer programs to gather and utilize knowledge independently of human input (Deutsche Bank Research, 2019), will revolutionize the banking sector. According to the McKinsey Global Institute, AI and machine learning will enhance decision-making, personalize services, and strengthen risk management, potentially generating over $250 billion in financial value within the banking industry (McKinsey & Co., 2019) (Atwal, Bryson, 2021: p.293).

Large language models (LLMs) are part of a class of language models that have demonstrated outstanding performance across a range of natural language processing (NLP) tasks (Fan et al, 2023: p.1). Currently, Large Language Models (LLMs) are recognized as valuable aides capable of automating routine micro tasks commonly undertaken by researchers throughout the day. LLMs excel in managing these tasks due to their rapidity and the cost-effectiveness associated with their utilization. Additionally, LLMs also serve as helpful mentors in coding and data analysis endeavors. By incorporating LLMs into their workflow, researchers can boost their efficiency. LLMs can offer guidance and assistance in programming and data analysis tasks, thereby simplifying and expediting the research workflow. However, humans still have a comparative advantage in assessing content credibility, accuracy, and context, necessitating human judgment and critical thinking. (Korinek, 2023: pp. 2-3).

Because of its adaptability, LLMs are a potential instrument that can be used in a variety of academic sectors and research areas. Rather than developing distinct supervised models customised for individual problems, scholars have adopted the use of LLMs to tackle a broad range of applications across numerous academic fields. With this method, a variety of tasks can be handled without the requirement for unique models for every task (Fan et al, 2023: p.4). The Language Learning (LLM) research field is constantly evolving, enabling scientists to tackle challenging language tasks in various sectors like medicine, engineering, social science, and humanitarian studies. LLMs are used in medical and engineering to analyze complex issues, such as automated software similarity analysis and disease research. Their effectiveness and adaptability demonstrate their potential in solving practical problems and promoting development across various industries (Fan et al, 2023: p. 20).

2.3 LLM potential in FinTech

Financial applications of artificial intelligence now have more opportunities thanks to recent developments in large language models. The application of LLMs in the finance sector could be advantageous since they can provide insights on trading, risk modelling, customer support, and other areas (Li et al, 2023: p.1). Research revealed that 77% of banks intend to significantly or substantially employ AI to automate tasks within the next three years (Accenture, 2018). This shift will necessitate a distinct, potentially revolutionary strategic direction from an organizational standpoint (Atwal, Bryson, 2021: p. 293). The ecosystem of fintech has witnessed the rise of innovative business models like crowdfunding and robo-advisory services, which have democratized access to funding and investment opportunities.

As fintech continues to evolve, it presents both opportunities and challenges for both traditional banks and consumers (Negi, 2023: p. e770).

Alfaro et al (2008) conducted a comparative study between artificial neural networks and AdaBoost for corporate failure prediction using a dataset of European firms. Adaboost is a machine learning algorithm that aims to improve the accuracy of classifiers by combining multiple classifiers into a single strong classifier (Zhu et al, 2009: p. 349). During training, Adaboost performs admirably at managing noisy data and outliers, producing a reliable model. Its ensemble technique facilitates risk assessment and decision-making. Its adaptability to a variety of datasets and issue types is ensured by its flexibility with alternative base classifiers, while retaining model interpretability, which is important for extracting actionable insights. Adaboost achieves state-of-the-art outcomes in a variety of classification tasks by striking a balance between bias and variance, resulting in dependable performance across varied datasets. It provides companies with a thorough and precise categorization solution, facilitating enhanced operational effectiveness and strategic decision-making (Alfaro et al, 2008: pp. 111-120).

Petrelli & Cesarini are suggesting a predictive model based on unsupervised clustering algorithms for data learning. The paper elaborates on the formulation of forecasting formulas based on the Petrelli-Cesarini index, tailored for high-speed forecasting in low time frames. It explores the implications of these methodologies for high frequency trading strategies, emphasizing the model's adaptability to varying time frames and trading frequencies. The model predicts financial asset prices using past data, aiming for accuracy. Widely used in various fields, especially finance, it minimizes error to achieve predictions ranging from over 50% to nearly 100% accuracy. The model is integrated into algorithmic trading, where an algorithm makes market decisions based on numerous parameters, primarily within the same field of application (Petrelli, Cesarini, 2021: p.249). The adoption rate of robo-advisory services, known for automated investment advice, has experienced a substantial increase, climbing from 5% in 2015 to 25% in 2023 (Negi, 2023: p. e772).

Artificial intelligence has transformed data analysis, facilitating predictive analytics, fraud detection, and the creation of robo-advisors for investment management (Negi, 2023: p. e770). Robo-advisors are arguably the most well-known among financial technologies. At the moment, algorithms used in robo-advisors provide advice on how much money should be saved, when to file for Social Security, which Medicare plan to select, and—above all—how to handle intelligent distributions throughout the decumulation stage of life. However, none of the robots on the market now can do all of these tasks with a single, straightforward system. These systems are positioned to close a major gap in advising services due to peoples acknowledged low levels of financial literacy and evidence that advice from human advisors is occasionally contradicted. Digital investment advising programs manage more than $200 billion in assets globally, according to Klass and Perelman (2019), who also stress that financial advice is fiduciary counsel (Agnew, Mitchell, 2019: p. 2).

Personalized financial insights can be given to users by LLMs through transaction history analysis. Based on the user's financial behavior, the LLM can provide insightful advice ranging from investment recommendations to budgeting instructions. Language Models can discern patterns of fraudulent activities through analyzing text data, including transaction descriptions and account activity. This proactive strategy aids in identifying potential threats and promptly notifying users. Processes like reviewing loan applications can be streamlined by LLMs. The model can save processing time for clients by providing faster and more accurate assessments by sifting through papers and contracts. Creating interesting and educational financial information can be facilitated by LLMs. LLMs can assist banks in offering their users informative material, like market updates or instructional articles about investing methods (Akyurek, 2023).

Trading and portfolio management have been among the earliest adopters of machine learning and deep learning models within the finance industry. The main goal of trading is to predict prices and generate profits based on these forecasts (Li et al, 2023: p. 2). By enabling organizations to make efficient use of both real-time transaction information captured at the point of sale and their previous customer data, deep learning is a viable answer to the problem of credit card fraud detection (Roy et al, 2018: p. 1).

Deep learning models and NLP techniques are widely applied in the field of financial text mining. The goal of financial text mining is to instantly extract meaningful information from vast amounts of unstructured data so that traders and risk analysts can make better decisions (Li et al, 2023: p. 2). Financial analysis applications have been studied, addressing the difficulty of accurately predicting financial text data. Main focus: classifying text data, analysis & application of results to forecast future news using data from market time series, forecasting stock prices (Fazlija, Harder, 2022: p. 2).

The main aspects of NLP are emotion recognition and sentiment analysis. These two names are not the same. Data can be evaluated to determine whether it is favorable, negative, or neutral using sentiment analysis (Nandwani, Verma, 2021: p.1). Stock price forecasting using sentiment analysis can benefit from the sentiment scores produced by cutting edge natural language processing techniques. There exist various instances in practice where the models presented here can be applied. The sentiment scores can be utilized for a risk-based approach, wherein a combination with other validated indicators is advised, since the scores should also reflect the sentiment of the market. The application of the NLP techniques discussed in connection with sustainable investing opens up still another avenue. Reports can be used, for instance, to determine whether an organization considers ethical or ecological issues. Consequently, a pre-selection of sustainable and less sustainable organizations can be established by automating the reading of the reports (Fazlija, Harder, 2022: pp. 17-18).

2.4 Cautions

Even though it can pick up techniques from the tamer, a circus tiger will always be a predator. Given that it is in their nature, the creature is not at fault if it harms or kills the tamer. Similarly, a T-800 is not at fault if it injures or kills a person since it is acting in accordance with its basic programming, which is comparable to an animal's instincts. Elephants are predator-free and among the rare animals with self-awareness, thus we can substitute tigers with elephants. Abuse can cause violent behavior to the point where elephants will kill people. Once more, the animal is not at fault, and having self-awareness does not affect who is responsible (Henz, 2021:p. 1). The gathering and utilization of extensive consumer data by Fintech companies have sparked notable privacy concerns. Critics express apprehension regarding the possible misuse of personal financial data, the risk of data breaches, and the perceived lack of transparency regarding the methods by which data is utilized and distributed (Negi, 2023: p. e773).

If the data used to train AI algorithms is incorrect or incomplete, it can lead to erroneous or biased decisions. For example, if historical data used to train AI models reflects biased lending practices or systemic disparities, the AI may perpetuate those biases. This can result in discriminatory outcomes in areas such as credit scoring, loan approvals, and other financial decisions. Factors such as race, gender, or location could influence AI recommendations or approvals if they were present in the biased training data.

Moreover, if the data used for training is not diverse or representative, it can further exacerbate biased outcomes, particularly impacting individuals from underrepresented groups. AI models can confuse correlation with causation, potentially leading to bias when using proxy variables related to protected characteristics like gender or ethnicity. For example, using postcode to determine credit eligibility may introduce bias as certain areas can be wrongly linked to particular demographics or socioeconomic factors (ICAEW Insights, 2023).

While innovation can stimulate economic growth and enhance financial inclusion, it also introduces new risks (Negi, 2023: p. e772). Responsible regulation and ongoing research play pivotal roles in shaping the future of banking and financial services, benefiting both institutions and consumers alike. Regulators have started adapting to this new landscape by implementing policies that foster innovation while simultaneously safeguarding consumer protection and maintaining financial stability. (Negi, 2023: p. e770). Davis and White discovered that policymakers are actively involved in adjusting regulations to accommodate the evolving Fintech landscape, frequently addressing concerns related to data protection, anti-fraud measures, and systemic risk management (Negi, 2023: p. e772). Handling and safeguarding vast amounts of sensitive financial data poses considerable challenges. It's imperative for both traditional banks and Fintech companies to prioritize robust cybersecurity measures to ensure the protection of customer data (Negi, 2023: p. e773).

Regarding the banking system, the situation is quite similar: getting user agreement and having clear communication regarding data usage are essential. Furthermore, to make sure that the confidence of customers is maintained, sensitive information must be handled carefully (Akyurek, 2023). AI might make privacy and data protection even more difficult. It might not be as easy as taking your name out of a database to remove the data that the AI learning techniques utilize from the model itself. In certain regions of the world, credit scoring systems that employ AI and big data to evaluate creditworthiness based on things like financial behavior, internet purchases, and social connections are already in use. These systems provide credit ratings to those who don't have traditional credit histories. AI can provide considerably wider access to financing for those in LEDC countries who do not use regular banking systems. To prove trustworthiness, the capacity to examine an AI model and comprehend how it makes decisions will be crucial in this regard (ICAEW Insights, 2023).

It is imperative to exercise caution when evaluating the capabilities of Large Language Models (LLMs), as they can be both easily overestimated and potentially hazardous. While LLMs can produce text that appears highly authoritative, it's crucial to acknowledge their propensity to "hallucinate" or generate entirely incorrect content. In human-written texts, an authoritative tone signifies insightful content. LLMs have learned to mimic this style without ensuring the reliability of the content. This presents a risk of leading unsuspecting readers to believe false or inaccurate content. LLMs possess capabilities that may appear unfamiliar to humans, primarily focusing on text generation. While their creators are actively working to enhance the truthfulness and appropriateness of generated content, this remains an ongoing challenge. Ensuring consistent accuracy and appropriateness in LLM-generated content is an area requiring continual development and refinement (Korinek, 2023: p. 3).

In sectors such as finance, the imperative to promptly analyze data in real-time is paramount. Any lag in processing would diminish the data's utility and its capacity to inform strategic business decisions (Arvind, Heinz, 2021: pp. 212-213). There are issues with LLM design and application, including computational difficulty, interpretability issues, and ethical considerations. To guarantee the appropriate creation and use of LLMs, there is a need to advocate for increased transparency and collaboration among stakeholders, including governmental organizations, academic institutions, businesses, data producers, and infrastructural service providers (Fan et al, 2023: p. 24). One drawback of traditional NLP techniques is that they struggle to process complex text and extended sentences. Nevertheless, these issues can be overcome by utilizing recurrent deep learning models and optimizing large language models (Fazlija, Harder, 2022: p. 2).

3. Evolution of Economical-Financial factors over the years for Romanian Banks

This section provides an overlook over the relevant financial information for investors and potential investors in tradable actions for two of the biggest Romanian banks, BANCA TRANSILVANIA SA and BRD - GROUPE SOCIETE GENERALE SA over the years 2021, 2022 and 2023. The choice has been made based on the financial dimension of the banks and availability of the relevant data.

3.1 Analysis of annual financial information for BANCA TRANSILVANIA SA

Table 1

Information for tradable actions **BANCA TRANSILVANIA SA**

	2023	**2022**	**2021**
SOCIAL CAPITAL	8,073,083,370	7,163,083,370	6,397,970,720
INTEREST EXPENSES	3,398,049,770	1,508,626,176	507,941,925
OPERATING EXPENSES	3,308,650,360	2,939,309,285	2,325,811,456
DEPOSITS FROM CUSTOMERS	134,443,350,078	116,503,841,609	102,698,085,035
BANK DEPOSITS	1,081,765,924	1,631,542,335	952,452,982
TANGIBLE ASSETS	755,412,552	731,036,689	652,580,851
LOANS FROM BANKS AND OTHER FINANCIAL INSTITUTIONS	8,583,795,225	3,562,483,030	7,457,842,606

Table created by author
Source: bvb.ro (see references)

There is a consistent year-over-year increase in social capital. This trend suggests the bank is strengthening its equity base, which is a positive sign. It indicates the bank is either retaining more earnings or successfully raising additional capital from investors. This growth enhaances the bank's ability to absorb potential losses and comply with regulatory requirements, signaling confidence in its prospects. The chart shows a dramatic increase in interest expenses over the three-year period. This significant rise could be due to the bank paying higher interest rates on deposits or borrowed funds, possibly reflecting a rising interest rate enviroment or increased competition for customer deposits. Alternatively, it might indicate a substantial increase in interest-bearing liabilities. This trend is concerning from a profitability standpoint and warrants further investigation into its impact on the bank's overall financial health. Operating expenses show a gradual increase each year. This upward trend is not unusual for a growing bank, as expansion often requires additional investments in staff, technology, and infrastructure. However, it's important to compare this growth rate with the bank's revenue growth to ensure expenses are not outpacing income. The slowing rate of increase in the most recent year could indicate improving operational efficiency or cost control measures.

Customer deposits had a robust and consistent growth over the three years. This is a very positive sign, indicating increasing customer trust and growing market share. It provides the bank with a stable and relatively low-cost source of funding for lending activities while suggesting the bank is successfully attracting and retaining customers in a competitive environment. The trend in bank deposits is more volatile, with an increase followed by a decrease. This fluctuation could reflect changing dynamics in the interbank lending market or shifts in the bank's funding strategy. It suggests the bank is adjusting its reliance on interbank funding based on market conditions, liquidity needs, or regulatory considerations. Tangible assets show a modest but steady increase year over year. This gradual growth suggests the bank is making consistent investments in its physical infrastructure, such as branch networks or IT systems. While the increases are not dramatic, they indicate ongoing commitment to maintaining and potentially expanding the bank's operational capacity. The Loans from Banks and Other Financial Institutions category shows significant volatility, with a large decrease followed by a sharp increase. Such swings could indicate that the bank is actively managing its funding mix, perhaps in response to changing market conditions or opportunities. The substantial increase in the most recent year might suggest favorable terms for institutional borrowing or a need to supplement funding sources to support asset growth.

3.2 Analysis of annual financial information for BRD - GROUPE SOCIETE GENERALE SA

Table 2

Information for tradable actions **BRD - GROUPE SOCIETE GENERALE SA**

	2023	**2022**	**2021**
SOCIAL CAPITAL	2,515,622,000	2,515,622,000	2,515,622,000
INTEREST EXPENSES	1,432,436,000	550,845,000	132,419,000
OPERATING EXPENSES	1,814,798,000	1,640,885,000	1,514,608,000
DEPOSITS FROM CUSTOMERS	62,641,838,000	56,915,740,000	52,917,886,000
BANK DEPOSITS	1,146,540,000	636,888,000	156,810,000
TANGIBLE ASSETS	1,051,237,000	1,046,443,000	1,051,254,000
LOANS FROM BANKS AND OTHER FINANCIAL INSTITUTIONS	6,079,625,000	3,567,262,000	2,230,572,000

Table created by author
Source: *bvb.ro (see references)*

The bank's social capital has remained unchanged over the past three years, holding steady at the same value. This constancy can be viewed as a sign of financial stability, indicating that the bank hasn't needed to raise additional equity capital. It suggests that the current capital base is sufficient to meet regulatory requirements and support ongoing operations. However, this lack of increase might also raise some questions from a growth perspective. In a dynamic banking environment, growth in capital is often expected to support expansion and new initiatives. The fact that the social capital has remained static could imply a conservative approach to growth, a reliance on organic growth through retained earnings, or limited opportunities for expansion in the market. Interest expenses have seen a dramatic rise over the three-year period, starting at a lower level and escalating significantly each year. This trend could be due to several factors. One possible explanation is a general increase in interest rates in the broader economy, which would raise the cost of the bank's borrowings and the interest it pays on deposits. Another possibility is that the bank is increasingly relying on interest-bearing liabilities to fund its operations. The substantial jump in interest expenses, particularly from the second to the third year, might suggest a major change in the bank's funding strategy or shifts in market conditions.

Operating expenses have shown a consistent upward trend, increasing steadily each year. This rise is not unusual in the banking sector, especially for a growing institution. Various factors could be contributing to this increase, such as the expansion of operations, investments in technology and digital infrastructure, increased regulatory compliance costs, or inflationary pressures on salaries and other operational expenses. The ongoing rise in operating expenses suggests that the bank is continuously investing in its operational capabilities. If operating expenses are growing faster than revenue, it could lead to decreased operational efficiency and reduced profitability.Customer deposits have shown strong and consistent growth over the three years. This is a positive indicator for the bank, suggesting increasing customer trust and potentially a growing market share. This trend is favorable as customer deposits typically represent a stable and relatively low-cost source of funding for banks. The steady growth in deposits could be the result of successful marketing strategies, competitive product offerings, or an overall improvement in the bank's reputation in the market. A larger base of customer deposits provides more resources for lending activities, supporting revenue growth.

The bank has seen a significant and consistent increase in deposits from other banks, which has grown substantially over the three years. This trend is noteworthy and could indicate improved standing and credibility in the interbank market. The sharp increase might suggest that the bank is becoming a preferred counterparty for other financial institutions, which is generally a positive sign. Alternatively, it could reflect a strategic decision to increase reliance on wholesale funding.Tangible assets have remained relatively stable over the three-year period, with only slight fluctuations. This stability suggests that the bank is maintaining its physical infrastructure and fixed assets without significant expansion or contraction. This could indicate a steady state in the bank's branch network and physical presence. The lack of substantial grrowth in tangible assets, especially when compared to the growth in deposits and other areas, might suggest a focus on digital banking or a strategy that doesn't heavily rely on expanding physical infrastructure.Loans from other financial institutions have shown substantial growth over the three years, increasing dramatically. This increase in borrowing from other financial institutions is a key point of interest. The bank might be responding to increased demand for loans by seeking additional funding sources or taking advantage of favorable borrowing conditions in the interbank market. The significant increase, particularly in the last year, suggests a major shift in the bank's funding strategy.

3.3 Conclusions

Banca Transilvania SA's increasing social capital strengthens its equity base, reflecting a robust ability to handle losses and meet regulations. However, rising interest expenses could impact profitability. The bank's growing customer deposits signal strong customer trust, while fluctuations in bank deposits and loans show active funding management. Modest growth in tangible assets suggests steady infrastructure investment. BRD - Groupe Societe Generale SA has maintained stable social capital, indicating financial stability but limited growth. The sharp rise in interest expenses could be due to higher rates or increased reliance on liabilities. Steady growth in customer deposits and significant increases in interbank deposits highlight growing market presence and credibility. Stable tangible assets suggest a focus on digital services over physical expansion, while increased loans from other institutions indicate a strategic shift in funding. Both banks are showing strengths in attracting customer deposits and managing operational expenses, but they face challenges with rising interest costs and the need to adjust their funding strategies. Banca Transilvania SA's increase in social capital suggests a focus on growth and resilience, while BRD - Groupe Societe Generale SA's stable social capital indicates a more conservative approach. Each bank's strategy has different implications for their future financial health and operational direction.

4. Research regarding use of financial technology based on Large Language Models

In this paper the author considered a two-step approach consisting of part one which is an indicative survey regarding the general interest regarding AI and the second part which is a comparative study between different AI-powered chatbots generating relevant information for businesses in the financial sector, such as novel concepts for financial services and products that meet unmet consumer demands or capitalize on new market trends or personalized financial solutions tailored to individual customers' preferences and circumstances.

4.1 Survey on use of Large Language Models in the financial sector

4.1.1 Methodology

The survey had demographic questions regarding age, gender, education level and current ocupation. These and question one, Likert-type question, meant to measure the respondent's level of familiarity with large language models, acting as independent variables for the study. The other questions were a mix of dichotomous (yes/no), multiple choice (select all that apply), Likert scale, and open-ended questions. The dependent variables were defined to analyze respondents' attitudes, perceptions, and opinions regarding LLMs. No incentive has been provided for anyone's participation to this study. Last but not least, identifying the challenges and limitations associated with using LLMs for creative ideation in the financial sector, including ethical considerations and regulatory implications. A purposive sampling approach was utilized to select participants who possess relevant experience and expertise in the subject matter. The sample size was determined to ensure adequate representation of the target population and statistical power in the analysis. The sample size is 122. Most respondents were over 18 years old, either students in one of the domains of interest, these being Business/Finance, IT/Technology, Research and Public Administration. The survey was administered online through various channels, including professional networks and social media channels. Participants were assured of the confidentiality of their responses and provided informed consent before participating in the study.

Quantitative data analysis was conducted using appropriate statistical methods and software. The Pearson correlation coefficient measures the strength and direction of the linear relationship between two variables. It ranges from -1 to +1, where:

- +1 indicates a perfect positive linear relationship,
- -1 indicates a perfect negative linear relationship
- 0 indicates no linear relationship

The chi-square (χ^2) test is a statistical test used to determine whether there is a significant association between two categorical variables. It's particularly useful for comparison between observed data versus expected data, to see if any differences between them are statistically significant. The test is based on the difference between observed and expected frequencies in one or more categories, and it's used to determine if there is a significant difference between the expected and observed frequencies.

4.1.2 Survey Results

The Pearson correlation coefficients examine various relationships concerning perceptions of Large Language Models in finance. Includes correlations between demographic factors, familiarity with LLMs, confidence in their capabilities, beliefs about their transformative potential in the financial sector, concerns regarding legal and ethical issues, and attitudes toward regulatory measures.

Table 3

Pearson Correlation for LLM Perceptions in Finance

	Pearson
Gender & Potential benefits	0.203
Revolutionizing financial sector & Confidence	0.374
Familiarity & Confidence	0.355
Education Level & Familiarity	0.414
Education Level & Revolutionizing financial sector	0.118
Familiarity & Revolutionizing financial sector	0.226

	Pearson
Gender & Concern legal/ethical	-0.026
Gender & Confidence	-0.026
Concern legal/ethical & Confidence	0.061
Current Ocupation & Use of financial tools	0.063
Current Ocupation & Regulatory Measures	-0.095
Use of financial tools & Regulatory Measures	-0.220

Source: Author

Gender and Opinion on LLM Benefits: There's a slight positive correlation (0.203) between a person's gender and their opinion on the benefits that large language models (LLMs) can offer for making business decisions. This means that gender does play a small role in shaping how individuals perceive the potential advantages of using LLMs in a business context, but the relationship is not very strong. Belief in LLMs' Transformative Power and Confidence in Data Interpretation: People who believe that LLMs can revolutionize financial strategies and decision-making tend to also have a moderate level of confidence (0.374) in the ability of LLMs to understand and interpret financial data accurately. This suggests that if someone is convinced of the transformative power of LLMs, they are quite likely to trust in their data interpretation capabilities as well. Familiarity with LLMs and Confidence in Data Interpretation: Those who are more familiar with the concept of LLMs generally exhibit a moderate amount of confidence (0.355) in LLMs' ability to interpret financial data accurately. In other words, the more people know about LLMs, the more confident they tend to be in the technology's data interpretation skills. Education Level and Familiarity with LLMs: The relationship between a person's education level and their familiarity with LLMs is very weak (0.041), indicating that there is almost no connection between how much formal education someone has and how well they understand LLMs. Education Level and Belief in LLMs' Transformative Power: There's a small positive correlation (0.118) between a person's education level and their belief that LLMs can revolutionize financial strategies. This suggests that those with higher education levels are slightly more inclined to believe in the transformative potential of LLMs, though the relationship is not very strong.Familiarity with LLMs and Belief in Their Transformative Power: If someone is familiar with LLMs, they are somewhat likely (0.226) to believe that LLMs can transform financial strategies and decision-making. This indicates a modest positive relationship between knowing about LLMs and believing in their strategic potential.

Gender and Concern About Legal/Ethical Implications: Gender has a very weak negative relationship (-0.026) with the level of concern regarding the legal and ethical implications of using LLMs in business decision-making. This means that gender barely influences how concerned people are about the potential legal and ethical issues associated with LLMs. Gender and Confidence in Data Interpretation: Similarly, gender shows a very weak negative relationship (-0.026) with confidence in LLMs' ability to interpret financial data accurately. This suggests that gender has almost no impact on a person's confidence in the data interpretation abilities of LLMs.Concern About Legal/Ethical Implications and Confidence in Data Interpretation: Concerns about the legal and ethical implications of LLMs have a very slight positive correlation (0.061) with confidence in their data interpretation abilities. This indicates that those who are worried about legal and ethical issues might slightly lean towards having more confidence in LLMs' data interpretation capabilities, but the relationship is very weak. Current Occupation and Use of AI Tools: The link between someone's current job and whether they use AI-powered financial tools is very weakly positive (0.063). This suggests that there is a tiny connection between the type of job a person has and their likelihood of using AI-driven financial tools, but it's not significant.Current Occupation and Opinion on Regulation:

There's a very slight negative correlation (-0.095) between a person's job and their opinion on the need for regulatory measures for LLMs. This means that people's current occupations have a minor influence on whether they think there should be regulations in place for LLMs, with those in certain jobs slightly less likely to support regulation. Use of AI Tools and Opinion on Regulation: People who use AI-powered financial tools are slightly more likely (-0.221) to have opinions against regulatory measures for LLMs. This indicates a weak negative relationship, suggesting that those who already use these tools may be somewhat opposed to the idea of introducing more regulations for LLMs.

Chi-Square test results showing the associations between variables related to perceptions of Large Language Models. It includes p-values and degrees of freedom for relationships such as gender and perceived benefits, confidence in LLMs, and familiarity with the technology.

Table 4

Chi-Square Test regarding Perception over LLMs

	Chi-Square	Degrees of freedom
Gender & Potential Benefits	1.8934E-191	15
Revolutionizing financial sector & Confidence	0	1
Familiarity & Confidence	0.999	1
Education level & Familiarity	0.999	1
Familiarity & Revolutionizing financial sector	1	1

Source: Author

In the conducted chi-square test of independence between Gender and respondent's opinion regarding what potential benefits LLMs offer for business-level decision-making [PotBen], a highly significant relationship was observed. The calculated chi-square statistic was found to be 1.8934E-191, with 15 degrees of freedom (df). This infinitesimally small p-value, essentially 0, provides robust evidence against the null hypothesis of independence between Gender and PotBen. During the chi-square test of independence between the Belief that LLMs can Revolutionize financial Strategies and Decision-making [Revo] and Confidence in the Ability of LLMs to Understand and Interpret financial Data accurately [Conf], no significant relationship was observed. The calculated chi-square statistic was found to be 0, with 1 degree of freedom (df). Therefore, based on this chi-square statistic, we cannot reject the null hypothesis, which states that there is no association between Revo and Conf. The chi-square test with 1 degree of freedom yielded a statistic of 0.999, indicating a moderate level of discrepancy between the observed and expected frequencies in the contingency table. However, this discrepancy did not reach statistical significance at the conventional alpha level of 0.05. Therefore, we fail to reject the null hypothesis, suggesting that there is insufficient evidence to conclude a significant association between familiarity with the topic and confidence in language models. The test with 1 degree of freedom yielded a statistic of 0.999, indicating a moderate level of discrepancy between the observed and expected frequencies in the contingency table. However, this discrepancy did not reach statistical significance at the conventional alpha level of 0.05. Therefore, we fail to reject the null hypothesis, suggesting that there is insufficient evidence to conclude a significant association between familiarity with the topic and the level of education. The chi-square test with 1 degree of freedom yielded a statistic of 1, indicating a moderate level of discrepancy between the observed and expected frequencies in the contingency table. However, this discrepancy did not reach statistical significance at the conventional alpha level of 0.05. Therefore, we fail to reject the null hypothesis, suggesting that there is insufficient evidence to conclude a significant association between familiarity with the topic and the belief that LLMs can revolutionize financial strategies and decision-making.

4.1.3 Conclusions drawn from the survey

The analysis revealed some notable relationships as well as an absence of strong associations between several variables related to perspectives on large language models (LLMs) in business and finance contexts. Moderate positive relationships were found between the belief in LLMs revolutionizing finance & confidence in their ability to interpret financial data accurately and the familiarity with LLMs & confidence in their financial data interpretation abilities.Weak positive relationships emerged between Gender & opinions on LLMs' potential business benefits and Education level & belief LLMs can revolutionize finance strategies. Very weak linear relationships were identified between: Education level & familiarity with LLMs; Concerns over legal/ethical implications & confidence in LLMs' financial comprehension; Occupation & encountering AI financial tools and Occupation & attitudes toward regulating LLM usage in business/finance.Gender exhibited very weak negative associations with legal/ethical concerns and confidence in LLMs' financial abilities. Notably, respondents with experience using AI financial tools tended to slightly disagree more with stringent regulation of LLMs for business compared to those without such experience. In essence, beliefs about LLMs' transformative potential and capabilities aligned more strongly, while demographics like gender and education exhibited weaker connections to viewpoints. Direct experience also appeared to influence regulatory attitudes.

4.2 Qualitative study about use of Artificial Intelligence in financial services

4.2.1 Methodology

The applications of artificial intelligence (AI) in the financial services industry has been rapidly expanding, with AI technologies being leveraged for tasks such as fraud detection, risk management, and portfolio optimization. One area of particular interest is the use of large language models (LLMs), which are AI systems trained on vast amounts of text data to understand and generate human-like language. LLMs have the potential to assist in generating novel ideas, analyzing complex financial data, and providing personalized recommendations. The study: Large Language Models (LLMs) have demonstrated remarkable capabilities in generating human-like text, exhibiting creativity and imagination in various domains. While LLMs have been primarily explored for tasks such as language translation, content generation, and question answering, their creative potential remains largely untapped in the financial sector. This study aims to investigate the potential of LLMs in generating novel and innovative financial products and services, challenging traditional approaches and fostering disruptive thinking in the industry. The study involves a comparison regarding the complexity, quality, usefulness and comprehensiveness of ChatGPT's and Claude AI's answers.

Objectives of the Study: this study aims to evaluate the performance of two state-of-the-art LLMs, ChatGPT and Claude AI, in generating ideas for innovative financial products and services, as well as developing plans for creating personalized financial solutions tailored to individual customers. Additionally, the study examines stakeholder perspectives on the potential impact and implications of using LLMs in business and finance contexts; Approach: Two LLMs, ChatGPT and Claude AI, were tasked with generating ideas for innovative financial products and services that address unmet customer needs or tap into emerging market trends. They were also asked to develop a plan for generating personalized financial solutions tailored to individual customers' preferences and circumstances.The ideas and plans generated by ChatGPT and Claude AI were evaluated based on criteria such as complexity, quality, usefulness, and comprehensiveness. The responses were compared to assess the relative strengths and limitations of each LLM in addressing the given tasks. Further details on the specific prompts provided to the LLMs and the full text of their generated ideas and plans are included in Annex A. A large amount of AI generated text has been added to this study for effective comparison purposes.

4.2.2 Study Results

For full answers see Annex A

Task 1: "Generate ideas for innovative financial products and services that address unmet customer needs or tap into emerging market trends."

Regarding Complexity, ChatGPT provided a more extensive list of 15 innovative financial product/service ideas, showcasing a broader range of concepts, Claude AI's list had 10 ideas, which were still diverse but slightly less comprehensive.

For Quality, both ChatGPT and Claude AI demonstrated a good understanding of unmet customer needs, emerging trends, and the potential application of technology in the financial sector. The ideas generated by both AI assistants were generally creative, relevant, and aligned with the task requirements. At Usefulness, ChatGPT's ideas covered a wider variety of financial domains, including investing, insurance, lending, personal finance management, and more, potentially catering to a broader audience. Claude AI's ideas were also useful but focused more on specific areas like personalized finance, sustainable investing, and alternative financing models. Comprehensiveness: ChatGPT provided more detailed descriptions for each idea, often including the unmet need, emerging trend, and a brief explanation of the concept; Claude AI's descriptions were more concise, which could be seen as either more focused or less comprehensive, depending on the perspective.

Overall, for Task 1, ChatGPT's response could be considered slightly more comprehensive, showcasing a broader range of ideas with more detailed descriptions, while Claude AI's response was still highly relevant and useful, albeit slightly more focused.

Task 2: "A plan for generating personalized financial solutions tailored to individual customers' preferences and circumstances."

Complexity: Both ChatGPT and Claude AI provided multi-step plans that addressed various aspects of personalized financial solution development; ChatGPT's plan had more granular steps (7 main steps with sub-steps), making it slightly more complex and comprehensive. For Quality, Both AI assistants demonstrated a solid understanding of the process required to develop personalized financial solutions, including data collection, analysis, solution development, implementation, and continuous monitoring. The steps outlined by both were logical, well-structured, and aligned with industry best practices.

For Usefulness, ChatGPT's plan covered a broader range of elements, including customer profiling, segmentation, product recommendation engines, advisory services, and leveraging emerging technologies like AI, ML, and blockchain. Claude AI's plan was also useful but focused more on the core aspects of data analysis, solution development, and customer feedback loops. Regarding Comprehensiveness, ChatGPT provided more detailed explanations and sub-steps within each main step, making its plan more comprehensive and easier to follow. Claude AI's plan was more concise, which could be seen as either more focused or less comprehensive, depending on the perspective.

4.2.3 Conclusions Drawn from the Study

Overall, for Task 2, ChatGPT's response could be considered more comprehensive, offering a more detailed and granular plan that covered a wider range of elements involved in developing personalized financial solutions. However, Claude AI's response was still highly relevant and useful, albeit slightly more concise. While both AI assistants performed well on both tasks, ChatGPT's responses were generally more comprehensive, providing more extensive lists of ideas and more detailed plans. However, Claude AI's responses were still of high quality and usefulness, showcasing a good understanding of the tasks and offering relevant and focused solutions.

5. Conclusions

The convergence of FinTech, AI, and Large Language Models (LLMs) is reshaping the financial landscape. While FinTech offers innovative solutions and LLMs promise automation and personalized insights, there are risks such as biased decision-making and data privacy concerns. Regulatory adaptation, robust cybersecurity, and transparent communication are crucial for navigating these challenges. Collaboration and ongoing refinement of these technologies are necessary to realize their potential while ensuring ethical and inclusive practices in finance.

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Annex A

Task 1: ’Generate ideas for innovative financial products and services that address unmet customer needs or tap into emerging market trends.’

Subject 1: ChatGPT

‘Green Investment Funds: Mutual funds or ETFs that exclusively invest in companies with strong environmental, social, and governance (ESG) practices; unmet Need: Growing demand for sustainable and ethical investing options; emerging trend: Increased awareness and concern for climate change and social responsibility. AI-Powered Personal Financial Advisors: AI-driven platforms providing personalized financial advice and planning based on user data and goals; unmet need: affordable, personalized financial planning for individuals without access to human financial advisors; emerging trend: Advances in AI and machine learning, increased comfort with digital services. Micro-Investment Platforms: apps that allow users to invest small amounts of money, even spare change, into diversified portfolios; unmet need: access to investing for individuals with limited funds; emerging trend: growth in mobile app usage, interest in democratizing finance. Cryptocurrency Insurance: insurance products designed to protect against losses from cryptocurrency theft, hacking, and volatility; unmet need: security and peace of mind for cryptocurrency investors; emerging trend: increasing adoption and acceptance of cryptocurrencies. Dynamic Credit Scoring Systems: Real-time credit scoring models that use a wider array of data points beyond traditional credit scores. Unmet Need: Fairer access to credit for individuals with non-traditional financial histories. Emerging Trend: Big data analytics and alternative data sources. Pay-as-You-Go Insurance: Insurance products with flexible premiums based on actual usage and behavior, such as driving patterns for auto insurance. Unmet Need: More affordable and tailored insurance options. Emerging Trend: IoT and data analytics providing more granular insights into user behavior. Real-Time Expense Management Tools for SMEs: Platforms that provide real-time tracking and management of expenses for small and medium enterprises (SMEs), integrating with accounting software; Unmet Need: Efficient financial management for small businesses; Emerging Trend: Digital transformation of small businesses, cloud computing. Blockchain-Based Identity Verification: Secure, blockchain-powered identity verification services for financial transactions and account opening; Unmet Need: Enhanced security and reduced fraud; Emerging Trend: Adoption of blockchain technology for security purposes. Health Savings Account (HSA) Investment Platforms: Platforms that allow users to invest their HSA funds in a wide range of investment options; Unmet Need: Better growth opportunities for health savings; Emerging Trend: Increasing healthcare costs and the need for proactive financial planning for health expenses. Subscription-Based Financial Education Services: Subscription services providing ongoing financial education, including webinars, workshops, and one-on-one coaching. Unmet Need: Continuous financial literacy and education; Emerging Trend: Lifelong learning and subscription-based models. Socially Responsible Lending Platforms: Peer-to-peer lending platforms that prioritize loans to underserved communities and socially responsible projects; Unmet Need: Access to capital for underserved markets and projects with social impact; Emerging Trend: Rise of social enterprises and impact investing. Integrated Financial Health Dashboards: Comprehensive digital dashboards that aggregate all financial accounts, credit scores, investments, and spending patterns, offering holistic financial health insights; Unmet Need: Simplified, holistic view of personal finances; Emerging Trend: Personalization and integration of digital financial services. Tokenized Asset Platforms: Platforms that enable fractional ownership of physical assets (e.g., real estate, art) through tokenization; Unmet Need: Access to high-value investments for smaller investors; Emerging Trend: Growth of blockchain technology and tokenization. Gig Economy Financial Solutions: Banking and financial services tailored for gig workers, including income smoothing, instant payments, and tailored retirement plans; Unmet Need: Financial stability and planning for gig economy workers; Emerging Trend: Expansion of the gig economy and non-traditional work arrangements. AI-Driven Fraud

Detection Services: Advanced fraud detection systems using AI and machine learning to identify and prevent fraudulent transactions in real-time; Unmet Need: Enhanced security and reduced fraud losses; Emerging Trend: Increasing sophistication of cyber threats and advancements in AI.'

(text generated by: https://chatgpt.com/)

Subject 2: Claude AI

'Personal Finance AI Assistant: An AI-powered virtual assistant that helps individuals manage their finances, track expenses, create budgets, and provide personalized financial advice based on their goals, income, and spending patterns. Micro-investing Platform: A user-friendly platform that allows individuals to invest small amounts of money regularly, enabling them to build long-term wealth gradually through fractional share ownership or micro-investment funds. Sustainable Investing Solutions: Financial products and services that facilitate investing in environmentally and socially responsible companies, such as green bonds, ESG (Environmental, Social, and Governance) funds, and impact investing opportunities. Peer-to-Peer (P2P) Insurance: A platform that connects individuals with similar risk profiles, enabling them to pool their premiums and share the costs of claims, potentially offering more affordable insurance options. Buy Now, Pay Later (BNPL) for Big-Ticket Items: Extending the concept of BNPL beyond e-commerce and retail purchases to larger expenses like home renovations, medical procedures, or education, providing flexible financing options. Personalized Financial Health Scoring: A service that analyzes an individual's financial data, including income, expenses, debt, and credit history, to provide a comprehensive financial health score and personalized recommendations for improvement. Blockchain-Based Cross-Border Payments: Leveraging blockchain technology to facilitate secure, transparent, and cost-effective cross-border payments and remittances, addressing the challenges of traditional international money transfers. Cybersecurity Insurance: Offering insurance products specifically designed to protect individuals and businesses against cyber threats, such as data breaches, ransomware attacks, and identity theft. Gamified Financial Education: A gamified platform that teaches financial literacy and money management skills through interactive games, challenges, and simulations, appealing to younger generations. Subscription-Based Financial Planning: Providing personalized financial planning services on a subscription basis, making professional financial advice more accessible and affordable for a broader range of individuals.'

(text generated by: https://claude.ai/chat/)

Task 2: 'A plan of generating personalized financial solutions tailored to individual customers' preferences and circumstances.'

ChatGPT: 'Understanding Customer Needs: Customer Profiling: Collect detailed information about the customer's financial status, goals, risk tolerance, spending habits, and life stage; Use surveys, interviews, and financial health assessments to gather qualitative and quantitative data; Segmentation: Segment customers into different categories based on their financial behavior, needs, and preferences. This could include segments like young professionals, families, retirees, etc. Data Collection and Analysis: Data Gathering: Use various data sources, including banking transactions, investment portfolios, credit reports, and lifestyle information. Ensure compliance with data privacy regulations like GDPR or CCPA when collecting and handling customer data. Analytics: Apply advanced analytics and machine learning techniques to identify patterns and predict future financial behaviors and needs. Use predictive modeling to forecast customer needs and recommend suitable financial products and services. Solution Development: Personalized Financial Planning: Develop customized financial plans that align with the customer's goals, whether it's saving for a house, planning for retirement, or managing debt. Offer a mix of products such as savings accounts, investment options, insurance, and loans tailored to their specific needs. Product Recommendation: Use recommendation engines to suggest financial products and services based on the customer's profile and predictive analytics. Ensure the recommendations are understandable and align with the customer's risk tolerance and financial objectives. Implementation and Delivery: Digital Platforms: Develop or enhance digital platforms (mobile apps, web portals) to deliver personalized financial solutions seamlessly. Provide interactive tools and calculators to help customers visualize their financial plans and make informed decisions. Advisory Services: Offer access to financial advisors who can provide personalized advice and adjustments based on changing circumstances. Use chatbots and AI-driven virtual assistants for immediate support and guidance.Continuous Monitoring and Adjustment: Regular Reviews: Schedule regular check-ins to review and update financial plans based on life changes (e.g., job changes, marriage, birth of a child). Provide alerts and notifications for important financial milestones and opportunities. Feedback Loop: Gather feedback from customers to continually improve the financial solutions and services provided. Use customer satisfaction surveys, NPS scores, and direct feedback channels. Enhancing Customer Experience: Education and Empowerment: Provide educational resources such as articles, webinars, and workshops to help customers understand financial concepts and make better decisions. Encourage financial literacy through personalized content and advice.Trust and Transparency: Build trust by being transparent about fees, product details, and potential risks. Ensure customers understand the value proposition and the rationale behind each recommendation. Leveraging Technology: Artificial Intelligence and Machine Learning: Use AI and ML to continuously improve personalization algorithms and predictive models. Implement natural language processing (NLP) for better understanding and responding to customer inquiries. Blockchain and Security: Ensure robust security measures to protect customer data and build trust. Explore blockchain for secure and transparent transactions.'

(text generated by: https://chatgpt.com/)

Claude AI: 'Customer Data Collection and Analysis: Gather relevant customer data, including demographic information, income sources, financial goals, risk tolerance, investment preferences, and any specific requirements or constraints. Analyze the collected data to identify patterns, trends, and customer segments. Customer Profiling and Segmentation: Develop detailed customer profiles based on the analyzed data, identifying key characteristics, behaviors, and preferences. Segment customers into distinct groups based on their profiles, allowing for targeted solutions. Product and Service Evaluation: Conduct a thorough evaluation of the available financial products and services offered by your organization. Assess the suitability, features, risks, and potential benefits of each product or service for different customer segments. Solution Development: Based on the customer profiles, segments, and product/service evaluation, develop personalized financial solutions that address the specific needs and preferences of each customer segment. These solutions may include customized investment portfolios, tailored insurance plans, personalized lending options, tax optimization strategies, or comprehensive wealth management plans. Solution Refinement and Testing: Refine the proposed solutions through iterative feedback loops, incorporating input from financial advisors, subject matter experts, and, if possible, a sample of customers from the target segments. Conduct pilot testing or simulations to assess the effectiveness and potential impact of the proposed solutions. Implementation and Delivery: Develop a robust implementation plan, including communication strategies, customer onboarding processes, and ongoing support mechanisms. Train financial advisors or relevant personnel to effectively communicate and deliver the personalized solutions to customers. Implement the solutions through various channels, such as face-to-face consultations, digital platforms, or a combination of both. Continuous Monitoring and Improvement: Establish mechanisms to monitor the performance and customer satisfaction of the implemented solutions. Gather feedback from customers and analyze their changing needs and preferences over time. Continuously refine and update the solutions based on the feedback and evolving market conditions, ensuring that they remain relevant and effective.'

(text generated by: https://claude.ai/chat/)