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Agentic AI in Financial Decision-Making: Enhancing Customer Risk Profiling, Predictive Loan Approvals, and Automated Treasury Management in Modern Banking

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Abstract

This essay investigates the role of agentic AI in revamping financial decision processes in modern banking. Specifically, three innovative applications of such technologies will be explored. First, an agentic AI financial expert has been developed to assist human risk managers in profiling customer credit risk. This can enhance accuracy by revealing biases and hidden inequalities of present profiling strategies. Secondly, an artificial analyst has been equipped with agentic AI technology to explore potential predictive loan approval using telephone calls from bank customers. Finally, agentic AI technology for treasury management improves the agility of a bank's response to capital fluctuations and therefore promises new ways for efficient cross-border multicurrency payment services. Overall findings indicate that agentic AI technologies are positioned to transform existing banking workflows in conjunction with traditional risk management practices – a revolution rather than a replacement. Fundamentally, agentic AI offers banks the opportunity to provide the modern financial customer with sophisticated self-service finance. Advancement in this area is necessary to remain competitive in an evolving digital banking landscape. Financial services that deploy agentic AI solutions offer improved and more personalized customer experiences, active and continuous risk management with fine-tunable outcomes, and higher efficiencies in treasury through automated asset and liability management. Thus, agentic AI has the potential to revolutionize banking beyond mere cost-cutting from automation, representing higher profitability through manyfold proven innovation.

Keywords: Agentic AI, Financial Decision Processes, Banking, Risk Management, Credit Risk Profiling, Predictive Loan Approval, Treasury Management, Capital Fluctuations, Multicurrency Payments, Artificial Analyst, Financial Expert Systems, Digital Banking, Self-Service Finance, Customer Experience, Automation, Asset Management, Liability Management, Financial Services Innovation, Profitability, Banking Workflows, Personalized Finance.

1. Introduction

One of the crucial elements of financial decision-making in retail and corporate banking is to understand the risks associated with the clients who borrow money from the bank’s balance sheet. Moreover, the banking industry uses financial technologies to improve risk management through intelligent systems that make more information available in an environment of increasingly volatile macroeconomic conditions. These developments pave the way for a financial organization that is allowed to know ever faster and to tackle a changing world much more effectively. In an increasingly competitive and dynamic banking sector, rapid and accurate risk profiling can help inform decisions and impact competitiveness to retain and grow one’s clientele.

In a risk assessment context, the assumption using machine learning or artificial intelligence to improve processes at a financial organization is conducted to optimize the process to better fit the customer/user and/or related stakeholders; maximizing the underlying business process supported by such technology, and exceeding the essential aspects of risk management. Concerning the latter, moving towards AI is a process that should be phased. The possible applications of agentic AI in financial operations from a cross-sector approach are far-reaching. More advanced AI can detect and prevent fraud operations, automate complex financial battlefield operations, and prompt useful information to critical prospects. This essay will therefore explain in more depth the potential for agentic AI when it comes to customer risk profiling, predictive loan approvals, and fully automated treasury management in the modern banking world.

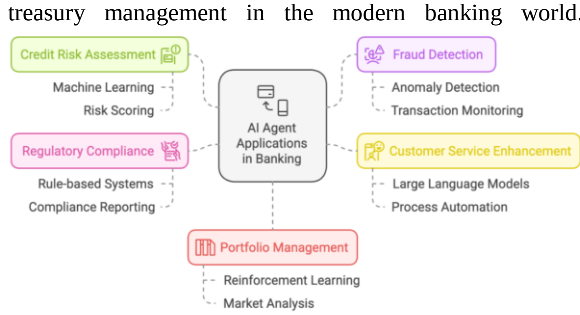

Fig 1 : AI Agentic Applications Transforming the Banking Sector

The use of machine learning and more advanced AI applications in the financial sector has been gaining ground throughout recent years and decades. The top motives for banks to apply artificial intelligence to more extensive activities like customer service, operations, or even automated decision-making are driven by the notion of being better equipped to meet the customers' needs. Moreover, the actual procedure could potentially result in easier consumer verification and user adoption. The use of AI technologies, in subjects of customer and cross-service, can have a beneficial effect, finally, on customer, officer, and shareholder satisfaction. The principal goal of artificial intelligence solutions in the financial environment is to gain from their sellable features in doing better business on a consolidated basis or in a supplier relationship.

1.1. Background and Significance of Agentic AI in Financial Decision-Making

Financial markets, consumer investment and cross-sell ecosystems have been changing continuously with increasing speed, driven by industry convergence, process megatrends, and technology acceleration. Financial services strongly depend on their ability to solve complex and evolving decision-making tasks with high precision, speed, and, if possible, at low labor costs. Even human intelligence has inherent limits to addressing the multidimensional, adaptive nature of the business of banking in the most accurate, efficient, and customer-friendly way. Therefore, for many years, there has been ongoing interest in adaptive rule and AI approaches as enablers of 'agentic' AI systems. But there is also a downside. Such adaptive rules and AI technologies can also become difficult to understand, potentially reducing the degree of freedom of managers to use their organization as they prefer.

Besides that, the topic of 'agentic AI' becomes even more relevant, as in our age, only real-time or near real-time responses can help avoid big losses. Even the best-confirmed indicators are most often outdated by many years, as their used data is often not current. The in-depth detail about recent developments, including their significant technical and regulatory implications, can be foundational for the establishment of forward-thinking strategic partnerships with banking industries and the security and bank supervisory institutions. Especially new regulations can act as market enablers or disablers for these agentic system concepts. In the future, banks may rely on intermediary companies, providing these agentic AI endpoints between themselves and the in-built new bank IT structures compliant under the different regulatory frameworks.

2. Theoretical Framework

Agentic AI is, at its simplest, AI that can act on our behalf, making decisions or carrying out functions without requiring human intervention or oversight. The presence of relatively slow-moving customers inhibits modern banking, and the employment of agentic AI in financial decision-making processes exhibits thus far an exclusive focus on enhancing that front-facing customer experience. In the present work, it is theorized that the potential of agentic AI in financial decision-making goes beyond an improved customer experience and may significantly alter the very means by which contemporary banking operations are conducted and assessed.

Several prevailing economic theories of innovation inform this analysis. Baumol's typology classically divides innovation strategies into three major categories. Agentic AI in finance can be understood as an example of technology design innovation, an innovation whose client or end-point user is also the innovation's first-order beneficiary. Similarly, transaction-cost analysis evidence on patents and market failures has shown that externalities preserving private returns to invention are particularly challenging in the service and technology-based sectors. As with Schumpeterian theories of innovation, much of the extant economics literature focuses on product rather than process innovation. For Schumpeter, the market was not nearly so contestably free as are the economic interactions of the Walrasians, and the nature of technological competition was, in Schumpeter's view, as likely to invest the realm of economic hegemony as sectoral profit itself. This has direct implications for the contemporary context of machine learning, where process innovation has certainly been monopolistically accrued and protected. In the present work, emphasis is given to the implications of agentic AI in the area of process innovation, particularly in light of modern conceptions of risk assessment practices.

2.1. Agentic AI and its Applications in Modern Banking

Agentic and naive AI technologies, specifically in the form of signal processing and control and filter systems, have further applications in financial and banking institutions. From the perspective of their operations, financial and banking institutions – credit institutions and insurance and investment companies – already use AI systems to support greater efficiency and productivity in the sale of their products, customer service, and process automation. Naive AI technologies are primarily represented by search applications (in the form of chatbots and voicebots), predictive analyses, and prescriptive or diagnostic tools, for example, in risk management and the prevention/identification of fraud or cybersecurity, within the sales process of investment products or in predictive proposals and approval of credit/loan applications, as well as in the automated management of treasury, for example, in the automatic online and real-time estimation of sums to be reconducted on current accounts and then invested in liquidity products, proposing the opposite operation, i.e., reinvesting in term deposits when the resources on current accounts exceed the usual amount, to customers. It is

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therefore useful to insert Agentic AI systems into banking financial institutions for the diagnosis of risk, the identification of predictive fraud or cyberattacks, and, as already mentioned, predictive proposals and the approval of funding applications or "market-oriented" operations such as the purchase or sale of investment products held for the bank's investment account.

Agentic AI technologies can be used to derive more efficient risk ratings thanks to the adaptation of the regression function for risk score determination, exploiting the potential of temporal sequences with recurrent networks. Agentic AI systems can also be applied to improving customer profiling, obviously within the strict regulatory constraints imposed by European legislation. For example, real-time financial management (revenues and expenses, tax operations, etc.) would allow banks to use the AI system to automate investment processes on sub-custody platforms up to real-time asset management services for end customers. The artificial neural network, through data sensing with connections in input, can be used for real-time daily forecasts of prices, exchanges, and commitments of orders, which manage automated trading algorithms using automatic investment policies (localized or dynamic investment including operations for capital appreciation and/or capital security), such as asset liquidation in the presence of dramatic market risk scenarios. Identifying the main trends and developments in the application of AI in banking financial institutions, at the end of this section, it will be useful to have a general reflection that allows the reader to orient themselves on possible future market trends in the application of these new technological tools and also helps in the reading of the topic. A look at the most widespread applications at the service of banking, linked to the main areas of business interest and innovation, leads to a topical reflection on the future of the banking market between AI, increased productivity, and recovery. Admin artificial intelligence and machine-learning tools to study customer economic and risk profiles, with interest as well as distribution. An appeal to use simple or Agentic AI to study and diversify investment risks. Created by a FinTech service dedicated to financial advisors who can propose diversified investments in public real estate funds to their clients.

3. Customer Risk Profiling

Building successful financial solutions is a complex and multifaceted task that benefits from automatic decision-making models. Nowadays, one of the processes that frequently includes automatic assessments is customer risk profiling. It helps to answer the questions of how risky it is to extend a loan to a particular client, shepherd available resources in the best risk/use ratio, and understand if a corporation has a safe credit history to invest extra money for efficient service with no defaults occurring. Machine learning provides AI software tools to adapt automatically over time. It continuously gathers and processes more data and can learn to identify even subtle pattern changes, especially those that could presage bad behavior in the network.

Inaccurate risk assessment can lead to a loss rate of 50% or more of the loan principal. Portfolio-wide, efficiently executed AI risk assessment can result in up to a 12% reduction in default rates. Customer profiling consists of traditional methods and modern AI/ML. Therefore, any investigated topic must draw comparisons and contrasts between the implementations and operations. User-based profiling results are stable for one type and widely explorative for another. A complex user-based risk assessment may include various factors in the risk cockpit, such as the contribution calculation classes, which are estimated based on reputation in real time. The classification and scoring help to develop a risk-scoring model and typology. AI can have verified portfolio probability rate reduction of about 12% in addition to the 50% reduction in default rates using new loan approval models. Long-term improvements are considered more significant in the long term. By combining behavioral patterns and diverse economic models, users are classified into defaults, meaning the good investment in the loan portfolio is reduced by lower loss capital than in another type. Case examples are available in various regions.

Fig 2 : Customer Risk Assessment

3.1. Traditional Methods vs. Agentic AI Approaches

1. Traditional Risk Profiling Tools Unlike a dynamic decision-making market, traditional methods consider what has been agreed upon or objectively exists. For example, banks' scoring functions use valuation grids as a tool from historical data and weighted score valuation of predefined risks to classify the default probability of customers. Unlike self-profiling with interactive data collection based on answers, a scoring function has a fixed set of criteria, and a yes or no payment decision is made at the end. Although historical data can be very rich, it cannot model economic and variable problems with "no warranty for the future," "non-obtainable data," "scarcity," and "no past performance." 3.1.2. The Agentic AI Approach Maturing out of the deterministic self-profiling line of development,

agentic AI solutions—in terms of data acquisition, the analysis of the collected data, and the decision-making applied—parallel the human decision-making market case. Just like humans, AI uses its algorithms to quantify different forms of information to identify relationships, establish inferences, and make predictions. This ability to assess risk in line with each market's specific characteristics defines a new research avenue. By exploring the potential of agentic AI capabilities, we argue that agentic AI combined with the newest and most robust hedging strategies can provide very accurate pre-decision market profiling techniques. 3.1.3. Limitations of Traditional Methods Lower speed and the subjectivity produced by high human interference represent the leading limitations of current profiling and credit scoring tools. Using these techniques in world markets can also be cumbersome without real-time integration into all stages of the financing activity, as real-time data is needed to correct and improve decisions. Banks also need to modernize their approaches to comply with the requirements of regulations, which use agentic AI reasoning to help clarify how financial institutions conduct market risk assessments. Ethical aspects are also important to consider, such as transparency in understanding decision-making done through agentic AI, so that the right of clients, in this case, to know their profile class is maintained, from the level of credit scoring to that of the readjustment of the rates and investment underwriter.

4. Predictive Loan Approvals

Traditional loan application platforms grant or deny loan applications by predefined cut-off values. However, this process is highly inefficient as it essentially evaluates a few applicants' creditworthiness at a time. Similarly, banks make use of scoring models that segment consumers based on demographic information. However, this system is not adaptive and does not account for changes in different segments and the economic climate. In so doing, the biases of race, gender, and empowered citizen techniques are automatically addressed. Automatic assessment of customer profiles is an immediate challenge in the modern banking sector. The presence of a considerable number of banking products by clients makes it difficult to describe customer profiles accurately. Loan performance is forecast slightly better when this wider information set is used. Automatic checks or gauges will be placed on credit and loans to manage the cash flow of the bank or lending institution.

Agentic AI, united with this new approach, mainly in the financial services sector, deals with different advanced analytics and AI/ML scenarios. Risk and compliance indicators are further enriched and translated into more than a dozen terabytes per day, and this electronic document encompasses more than two full customer financial conveyances, policy schedule contracts, and impression sign images. Agentic AI and these advanced statistics are directly related to the extent to which credit policies and finite provisions are determined, mainly by using customer-level individual information at the lowest level to adjust the amount of money or interest rates to keep rates for each credit transaction to a minimum and the effect on the automobile or consumer portfolio. The number of credit applications approved and allowed is determined to some extent based on the guidelines; subjects with the highest traditional and agentic AI scores are generally subject to the best overall scientific scores. The approval rate for each application is determined using substitution methods. Retrospection shows that 95% of pieces from the unbalanced panel are used for the evaluation, with 10% of data held out for validation during a period. Applications for the highest and lowest scores accordingly account for a relative majority. Changes in the various segments are also transformed up and down. An automated cloud SaaS data science solution based on Agentic AI can also be modeled; this solution is called Automated Machine Learning.

4.1. Challenges in Traditional Loan Approval Processes

The traditional approach to lending often presents a series of issues, from having slow or hard-to-understand processing systems to making trade-offs between efficiency and fairness, or from increasingly falling back on credit scoring methods that originated before the age of the internet to adopting new decision-making processes that could be heavy in compliance costs. A review of current loan approval practices highlights a series of problems. Accurate risk assessment is of mutual importance to lenders and borrowers as the secret glue of lending and borrowing. Traditional loan approval processes often rely on credit scores, greenfield models originally addressing in-store catalog shopping from more than 60 years ago, and introduce a degree of arbitrariness, for hidden features of modern decision-making processes, are very hard for potential candidates to predict. Such processes are of pressing importance because a 1% improvement in credit decisions by a universal bank with a tens of billion euros-sized loan book retains an extra amount over 10 years compared to holding a loan on decision outcomes that are objectively incorrect but favor the applicant.

In some instances, credit scoring models used in lending decision-making could be indirectly biased as they may favor the wealthy while excluding or disadvantaging the less wealthy, students, and household debtors; earlier versions of loan approval models before the introduction of machines were based on the Six Cs of Credit, such as capacity, capital, condition, collateral, character, and cash flow. Credit scoring activities by financial institutions are subject to regulations; the regulation has introduced a right to decision-making, potentially making it costly to reduce algorithmic liability or to become socially accountable for underlying decision-making processes. Interestingly, numerous industry reports on banks and their practices of adopting in-house developed or off-the-shelf AI and machine learning applications or of outsourcing model development and validation functions sit within the sphere of regulatory technology innovation, competition, and collaboration or about creating interconnected ecosystems, though do not focus on the creation of new business models, consumption models, or on risks to social security associated with traditional corporate job cuts or offshoring based on traditional cost reduction practices. Therefore, to increase the appeal and thus the employee must follow the AI principles and values at all times, akin to the idea of environmentally friendly investing. The fear of increasing compliance costs was shown by two heads of a discussion paper on the development of credit risk assessment modeling too. The prevalence of such beliefs shows that AI in finance could in part be about reducing application processing periods and decision uncertainty as a result. With this in mind, it is clear that there is an increasing demand to do things differently to make loans more efficient and, in some modern approaches, fair.

5. Automated Treasury Management

Contemporary banking places greater emphasis on the management of banking functions such as operational risks, financial assets and liabilities, market risks, and treasury functions. Corporate digital cash management plays an essential role in bank treasury functions to attract and maintain corporate clients. The current approach of corporates in digital cash management and the overview of the applicability of AI for cutting-edge treasury management systems are presented. AI-based recent trends show that these AI technologies are a subfield of computer science that takes up the challenge of solving "hard" problems more efficiently and has shown success on financial platforms and systems in the banking sector. Agentic AI that learns from data behaves rationally, makes "good" decisions, and communicates with end-users by 2025 is possible.

In contemporary operations of bank treasury, the integration of digital systems with cutting-edge hardware and software systems, as well as workflow and communication systems, forms an essential part of efficient banking operations in general and treasury functions in particular. Automated treasury systems can yield much greater functioning compared to manual processes. AI technologies form an essential part of the cutting-edge banking treasury system to perform liquidity management operations and financial transactions in an entirely different and unexpected way in real-time, storing, processing, and describing critical and relevant data within the blink of an eye. Enabled by AI technologies, the combined knowledge base of human beings is used in treasury management operations. The process of sending digital requests for transactions for financial operations to be executed and responded to in real time by the projected channel and source is called the digital request response.

With the current technological scenario, data takes a special place influencing every domain driven by technologies. The on-demand real-time analysis of operating cash liability positions and forecasting liquidity management operations yield an optimized funding plan. Float balancing in case of urgent fund requirements and adopting strategies to move funds across accounts pushed with minimal interest margins or float prioritized thresholds would be clear and accurate. The proposed system will create a revolutionary platform to monitor financial strategies, operations, and effectiveness of the generated alerts, and assist end-users to act in real-time to adopt the strategies needed or adjuvants. A sudden change in customer purchasing patterns and payment behavior, or the effect of sudden recessions due to economic shutdowns can disturb firms' cash cycle activities affecting liquidity positions. As a result, balancing cash float position balances becomes difficult owing to the incapability of carrying out day-to-day strategic operations of the firm. Effects arising from the working capital management system, which ties up most of a firm's liquid assets, are expressed through different cash conversion cycles.

5.1. Benefits and Challenges of Implementing Agentic AI in Treasury Management

Equipped with new agentic AI empowered by the Enactive AI generation, banks can leverage this development to achieve customer identification, risk profile, and pricing more accurately, and in turn offer context-sensitive loan contracts. Furthermore, by accelerating the automation of business operations, including customer risk assessment and loan approval, and providing actionable insights into working capital demands, it can undertake treasury management at ever-decreasing costs. Despite these opportunities, agentic AI presents challenges in the areas of processing power and data acquisition. Additionally, the adoption of agentic AI into bank treasury operations has disadvantages in employee professional development and possible changes in employees' work situations that may negatively affect their stance towards the aims and goals of their employer. The challenges of integrating and implementing agentic AI in treasury management include secondary costs of the initial investment, the duration of investment financing, the training of bank employees, and the costs of user interfaces between systems and digital platforms. The gradual nature of the benefits of agentic AI applications implies a gradual exposure to the risk of implementing agentic AI. Essential conditions for integrating and implementing agentic AI into bank treasury

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must be met: proposition and demonstration of the efficiency of agentic AI-enhanced treasury management; ensuring transparency on both technical and ethical conditions; and the development and adoption of regulatory requirements for business operations, data privacy, and ethical social and ecological aspects.

6. Case Studies and Practical Implications

The purpose of technology innovation in banking is to offer prospects of matching or even surpassing existing customer expectations and standards. One can label innovations as novel gadgets, wagering on the assembly and commercialization of new products, or else, as practice amplification aiming to improve a certain work system. In the following, we shadowed the way banking consumer services considered deploying Agentic AI systems both in technology laboratories and major commercial banks. This includes automated risk profiling of hard and soft data, predictive loan approval systems, and automated FX risk hedging for corporate clients. In this way, operational marketing technology solves issues on both a low, immediately realizable level and on a high, problem and vision-oriented level. We turn to the long-term horizon of research work with clients and in institutions' laboratories.
The case studies have offered a comprehensive overview of the development and commercialization of robotics in banking. Moving directly to end consumer service solutions, however, is still in the early phases of development and requires creative exploration of customer systems and attitudes towards exact solutions. Technology drivers outline that three lessons learned are universally valid: First and foremost, we have learned that Agentic AI solutions have always been designed with an eye to the specific context, thus either commercial bank specifications, customer processes, or tech providers' strengths. Also driven by banking specifications, the systems have usually shown scalability in terms of extending the number of clients but occasionally also proved potential for extension from individual to fear customer services. The Agentic AI solution partners with the participating bank. In terms of market positioning of Agentic AI solutions, commercials may be used either to enrich individual service packages or to streamline mass processes. Up until today, Agentic AI applications have mostly been used as extensions for particular premium service packages. Several solution providers and commercial banks, however, opened a new market segment that deals with low-end mass process commercial Agentic AI applications in money transfer and FX trading.

6.1. Real-world Examples of Agentic AI Implementation in Banking

The banking sector is aware of the benefits of integrating the latest emerging technologies, including blockchain, biometrics, and artificial intelligence. In this section, we provide a few examples of how AI is currently employed in banking, resulting in an evolved or completely new way to operate. Below are several use cases that confirm that banks are continuously innovating to keep up with market trends and client needs. Agentic AI has the potential to fill these gaps and challenge the traditional roles of bank employees.

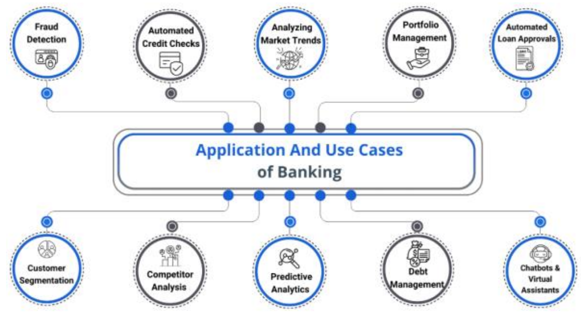

Fig 3 : Banking Operations with Agentic AI

A bank introduced ALEX, the AI Lend Express, in early 2020. ALEX is AI-driven and allows for the approval of business loans of up to SGD 100,000. This can reduce a lot of paperwork and time taken from three hours to 90 seconds for the approval of business loans. ALEX also provides a suite of treasury management solutions that are designed to assist finance professionals in assessing potential account receivables by their customers. The client can use the Spectrum tool for candidate selection to test their customer profiling via the advanced intelligence-led credit risk system. ALEX leverages AI to help SMEs improve their trade and cash management to approach known business partners or identify potential fraud by checking if a particular deal involving goods has had any untoward events in history, such as financial delinquency, court disputes, and more. Customers can also look up settlements to keep track of the sum they will receive, and via the ATEX, advance an amount to cover their cash flow requirements while awaiting their cash.

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