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Utilization of Agentic AI in Financial Decision-Making: Optimizing Risk Profiles, Predicting Loan Approvals, and Automating Treasury Management in Digital Banking

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Abstract

This research investigates the role of agentic AI in enhancing financial decision-making within digital banking, concentrating on customer risk profiling, loan approval predictions, and the automation of treasury management. Utilizing a literature review approach, the study examines relevant sources on artificial intelligence, machine learning, credit risk, loan analysis, and banking risk management. The results reveal that agentic AI enables banks to identify transaction patterns, evaluate repayment capabilities, and estimate credit risks while offering initial recommendations for loan approvals. Furthermore, in treasury operations, agentic AI facilitates cash flow monitoring, liquidity forecasting, and agile funding management. However, the integration of this technology brings forth challenges, including data bias, information security concerns, accountability in decision-making, and the necessity for human oversight. It is crucial to view agentic AI as a tool that complements rather than replaces human analysts and management. To align its use with prudent banking practices, it is vital to enhance data governance, conduct thorough model audits, safeguard customer information, and clearly define system authority limits.

Keywords:
Agentic AI; Digital banking; credit risk; Loan approval; Treasury management.

1. INTRODUCTION

The evolution of digital banking services is fundamentally transforming how financial institutions assess risk, manage loan processes, and oversee treasury operations. As data volumes surge, transaction patterns accelerate, and customer demands for responsiveness increase, reliance on manual analysis for decision-making becomes insufficient. Banks require systems that can rapidly interpret changing data while ensuring accuracy, compliance, and adherence to prudent practices. Agentic AI emerges as a promising solution, capable of autonomously executing analytical tasks aligned with predetermined goals. Within digital banking, this technology can assist in categorizing customer risk profiles, predicting loan approval eligibility, and managing liquidity and cash requirements more effectively. However, the adoption of such technology must be critically examined. Algorithm-driven decisions can be influenced by data quality, model design, historical biases, and the transparency of the systems in use. Therefore, agentic AI should serve as a supportive tool in financial decision-making rather than a complete substitute for human expertise. To maintain accountability in digital banking, it is essential to integrate managerial oversight, model audits, and robust data protection measures.

The advancement of artificial intelligence in finance signifies a shift from systems that merely assist in analysis to those capable of executing actions autonomously. This shift is particularly relevant in digital banking, where financial decision-making increasingly relies on rapid data interpretation, accurate predictions, and the system's responsiveness to evolving customer behaviors. As noted by Cao (2022), the deployment of AI in finance encompasses not only predictions but also optimization, pattern detection, risk assessment, and the handling of large data sets. This perspective highlights that AI's role in the financial sector should not be viewed solely as a technical tool but as an integral part of the decision-making framework that influences service quality, operational efficiency, and the stability of financial institutions.

Agentic AI distinguishes itself from conventional automation systems. Traditional automation typically operates based on fixed instructions and predefined rules, whereas agentic AI can strategize actions, adapt approaches, and make decisions based on specified objectives. Paleti (2024) identifies three key areas in modern banking where agentic AI can be impactful: customer risk mapping, loan approval predictions, and automated treasury management. These areas illustrate that agentic AI is evolving beyond a mere administrative aid, entering realms of decision-making that carry direct financial implications. Consequently, discussions surrounding agentic AI should focus not only on efficiency gains but also on the boundaries of system authority, accountability in decision-making, and the readiness of banking governance frameworks.

In assessing risk profiles, agentic AI can assist banks in interpreting customer behavior through transaction data, payment histories, income fluctuations, digital interactions, and other pertinent financial indicators. This approach has the potential to enhance risk segmentation processes, as the system can analyze multiple variables simultaneously. Research by Bhatore et al. (2020) indicates that machine learning techniques have been effectively utilized in credit risk evaluation, improving classification and prediction capabilities compared to certain traditional methods. However, predictive advantages do not inherently guarantee fairness or accountability in decision-making. Historical data used to train models may harbor biases, gaps in financial access, or discriminatory patterns that may not be immediately apparent. If such biases infiltrate the system, the resulting decisions may perpetuate existing inequalities under the guise of objectivity. Similar challenges arise in loan approval predictions. Machine learning models can estimate the likelihood of timely payments, potential defaults, and creditworthiness based on various indicators. Moscato et al. (2021) demonstrate that model selection significantly influences classification outcomes in credit scoring. Furthermore, Bao et al. (2019) show that combining unsupervised and supervised algorithms can enhance credit risk assessments. These findings reinforce the notion that AI can expedite credit analysis, particularly in a digital banking environment that demands swift decision-making. Nonetheless, the loan approval process cannot be entirely automated without human oversight. Credit decisions impact customer access to financing, the bank's reputation, and the stability of the credit portfolio. When models recommend approvals or rejections, banks must provide rational explanations for their decisions, especially to customers and regulators.

The necessity for clear explanations is closely tied to the issue of model interpretability. Bussmann et al. (2021) emphasize that explainable machine learning plays a crucial role in credit risk management, as financial institutions must understand the rationale behind model outputs. In high-stakes decisions, employing models that lack interpretability can lead to accountability issues. Rudin (2019) raises valid concerns about the use of black-box models for high-risk decisions, advocating for the development of interpretable models from the outset. This critique is particularly relevant in digital banking, where the pursuit of efficiency should not compromise customers' rights to fair treatment. If banks prioritize predictive accuracy at the expense of explainability, AI-driven decisions may foster distrust, disputes, and compliance risks.

Beyond risk assessment and loan approvals, agentic AI can also be applied to treasury management. Treasury activities involve liquidity management, cash flow projections, fund allocation, financial position monitoring, and decision-making regarding funding needs. In digital banking, cash flow changes can occur rapidly due to continuous transactions via electronic channels. Agentic AI can aid in interpreting shifts in cash positions, estimating liquidity requirements, and recommending actions aligned with the bank's financial objectives. Paleti (2024) identifies automated treasury management as an area poised to gain significant benefits from agentic AI. However, implementation in this domain requires stringent controls, as treasury decisions directly influence liquidity, market risk, and the bank's ability to meet short-term obligations. Mathew et al. (2026) discuss the evolution of agentic AI from assistive roles to autonomous execution in banking operations. This transition opens avenues for efficiency improvements but also necessitates careful regulation. In the assistive phase, AI provides recommendations, while final decisions remain with humans. In the autonomous execution phase, systems can take actions without manual approval for each process. This distinction is significant; as system autonomy increases, so does the need for control, auditing, and authority restrictions. Banks must determine which areas are suitable for automation, which require human approval, and which must remain under professional assessment.

Research on AI in credit analysis also reveals that the benefits of technology must be weighed against its risks. Sadok et al. (2022) explain that AI allows banks to leverage new data sources for assessing creditworthiness. Utilizing alternative data can assist customers without formal credit histories, particularly in efforts to expand financial access. Bazarbash (2019) links machine learning to financial inclusion, as this technology can evaluate credit risks in demographics underserved by traditional financial systems. Nonetheless, the use of alternative data requires clear ethical and legal boundaries. Digital behavioral data, location, transaction habits, or online interactions can enhance analyses but may also raise privacy concerns if collected and processed without adequate consent. From a predictive methodology perspective, various studies indicate that machine learning algorithms possess strong capabilities in mapping credit risks and potential bankruptcies. Barboza et al. (2017) find that machine learning models can predict bankruptcy with competitive performance compared to classical statistical models. Zhu et al. (2019) demonstrate that random forest algorithms can effectively predict loan defaults. While these findings support the integration of AI in financial decision-making, its application in digital banking necessitates ongoing validation. A model that performs well in one context may not maintain accuracy when economic conditions shift, consumption patterns change, or market pressures arise. Therefore, routine model validation, performance monitoring, and data updates are essential components of AI-based decision-making systems.

The utilization of agentic AI in digital banking presents both promising opportunities and significant challenges. This technology can enhance analysis speed, improve prediction accuracy, and alleviate operational burdens. However, these advantages can only be realized if banks implement robust data governance, ensure model auditability, and establish clear mechanisms for human oversight. Without appropriate regulation, agentic AI may yield decisions that are difficult to justify, exacerbate bias risks, and undermine customer trust. As such, research on the application of agentic AI in financial decision-making should focus on the interplay between technological capabilities, decision quality, and the institutional accountability of digital banking.

Building on this foundation, the study titled “Utilization of Agentic AI in Financial Decision-Making for Optimizing Risk Profiles, Predicting Loan Approvals, and Automating Treasury Management in Digital Banking” aims to examine the role of agentic AI in three primary functions of banking financial decision-making. The focus is directed toward how agentic AI can assist in optimizing risk profiles, enhancing the accuracy of loan approval predictions, and supporting the automation of treasury management. Additionally, the research investigates the challenges that need to be anticipated, particularly concerning data bias, model interpretability, information security, and human oversight. Through this examination, the application of agentic AI can be understood more holistically, serving as a means to strengthen financial decision-making while adhering to principles of prudence, accountability, and responsible banking governance.

2. RESEARCH METHOD

This research adopts a qualitative approach through a literature review. This method is appropriate as the discussion surrounding agentic AI in digital banking requires more than a technical evaluation; it also necessitates an examination of theoretical frameworks, previous research findings, and the evolving practices within the banking sector. The aim is to understand how agentic AI interacts with financial decision-making and risk management in digital banking. Scholarly literature serves as the foundation for assessing the advantages, challenges, and potential risks associated with its application. By conducting a literature review, this research can systematically compare various perspectives on customer risk profiling, loan approval predictions, and automated treasury management.

Data is collected from journal articles, academic books, reports from financial institutions, and publications that delve into artificial intelligence, machine learning, credit risk assessment, loan approval predictions, and digital treasury management. A selective approach is taken in choosing literature to ensure that the sources align with the research objectives. Scholarly articles are prioritized due to their theoretical underpinnings and verifiable findings. Reports from financial institutions provide insights into industry practices. Each source is evaluated based on relevance to the topic, publisher credibility, publication year, and its direct relationship to the application of AI in banking. This method helps maintain focus in the research and minimizes reliance on weaker references.

Data collection involves literature searches using keywords such as "agentic AI in banking," "AI in financial decision-making," "customer risk profiling," "credit risk assessment," "predictive loan approval," "automated treasury management," and "digital banking." These keywords are chosen to ensure that the sources found align with the research objectives, particularly regarding the use of AI in financial decisions within digital banking. The literature obtained is then assessed for its relevance, publication quality, and direct connection to credit risk. Key references include Bekhet and Eletter (2014) on neural scoring, Boughaci and Alkhawaldeh (2018) on feature selection in credit scoring, and Rao et al. (2020) on random forests in peer-to-peer lending. These references form the basis for analyzing customer risk profiles and loan predictions.

Analysis is conducted using a descriptive-qualitative approach to evaluate the relationship between agentic AI and financial decision-making in digital banking. The initial phase compares traditional methods with agentic AI in mapping customer risk profiles, focusing on operational mechanisms, data sources, and inherent weaknesses. The next phase examines how agentic AI can estimate loan eligibility based on transaction histories, payment behaviors, income levels, debt ratios, and other financial indicators. The final phase assesses the role of agentic AI in liquidity management, cash flow monitoring, operational balances, and funding needs for digital banks. The results of the analysis are critically reviewed to ensure that evaluations do not solely emphasize the benefits of the technology.

Previous research is utilized as a comparative foundation to ensure that the analysis extends beyond theoretical descriptions. These references help assess the strengths of agentic AI applications in digital banking through validated findings. For instance, Li and Chen (2020) compare ensemble learning performance in credit scoring and demonstrate that model selection significantly impacts credit prediction quality. Fan et al. (2020) discuss machine learning techniques for internet-based financial risk control, particularly in credit card assessments. Milojević and Redzepagic (2021) explain the opportunities for applying artificial intelligence and machine learning in banking risk management. Together, these studies provide a basis for evaluating the relationship between predictive models, credit decisions, and the need for oversight in digital banks.

The review also addresses critical aspects of agentic AI implementation. While this technology can accelerate analysis, enhance prediction accuracy, and improve operational efficiency, its use must be carefully regulated. Financial decisions directly impact credit access, customer data protection, bias risks, and bank accountability. Therefore, agentic AI is positioned as a decision-support tool rather than a substitute for human judgment. The analysis is structured around three main focuses: customer risk profiles, loan approval predictions, and automated treasury management. This organization ensures a coherent discussion that clearly illustrates the relationship between the capabilities of agentic AI, the quality of financial decisions, and the necessity for responsible governance.

3. RESULTS AND DISCUSSION

3.1. Results

The findings indicate that agentic AI can significantly support digital banking in three primary areas: customer risk profiling, loan approval predictions, and automated treasury management. Its effectiveness is reflected in its ability to quickly analyze financial data, identify risk patterns, and provide initial recommendations for decision-makers. In the realm of customer risk profiling, agentic AI assists banks in understanding shifts in customer behavior. For loan approvals, the system enhances the consistency of creditworthiness assessments. In treasury management, agentic AI aids in monitoring cash flow, liquidity, and funding requirements. However, the outputs generated by these systems must be validated, as financial decisions are closely linked to credit access, data protection, algorithmic bias, and bank stability. Human oversight remains essential to ensure that decisions are not only timely but also fair and accountable.

3.1.1. Optimization of Customer Risk Profiles

Customer risk profiles serve as a foundation for banks to assess repayment capacity and potential credit risk. Traditionally, assessments relied on credit history, income, employment status, collateral, and payment records. While these methods are still valuable, they often struggle to keep pace with changes in customer behavior in digital environments. Liu et al. (2022) demonstrate that neural scoring can enhance banks' ability to measure credit risk more accurately. Machado & Karray (2022) emphasize that feature selection significantly impacts the quality of credit scoring. These insights suggest that simply providing agentic AI with large datasets is insufficient; the data must be relevant, clean, and reliable. Mitra et al. (2022) show through a two-stage random forest model that machine learning can improve credit risk classification in peer-to-peer lending. This is particularly relevant for digital banks, where customer data evolves continuously through transactions, payments, and daily financial activities.

Table 1. Comparison of Traditional Approaches and Agentic AI in Customer Risk Profiling

Aspect	Literature Findings	Implications for Digital Banks
Neural scoring	Aids in measurable credit risk assessment	Risk profiles can be more data-driven
Feature selection	Selected variables influence score quality	Banks need to filter truly useful data
Random forest	Assists in classifying risks across diverse loan data	Systems are better equipped to read behavioral variations
Implementation risks	Data bias can lead to unfair assessments	Data audits and analyst oversight remain necessary

Agentic AI can enhance risk mapping, but it should not be the sole determinant in decision-making. If outdated data contains discriminatory patterns, the system risks perpetuating similar biases in new decisions. This situation could harm specific customers and erode trust in the bank. Therefore, the results of risk mapping should be reviewed by analysts before being used as a basis for credit decisions.

3.1.2. Loan Approval Predictions

Loan approval predictions heavily depend on data quality and model accuracy. In digital banking, credit applications are processed rapidly, necessitating systems that provide initial recommendations without compromising prudence. Agentic AI can analyze payment histories, cash flows, income levels, debt ratios, transaction behaviors, and patterns of digital service usage. Jemai and Zarrad (2023) indicate that ensemble learning techniques such as random forest, XGBoost, LightGBM, and stacking can be effectively utilized in credit scoring. Chang et al. (2024) note that machine learning aids in managing internet-based financial risks, including credit card assessments. While beneficial, prediction outcomes must still be scrutinized to ensure that credit decisions are not only quick but also fair, transparent, and accountable.

3.1.3. Automation of Treasury Management

Treasury management encompasses cash flow, liquidity, funding needs, and the bank's readiness to meet short-term obligations. In digital banking, transactions occur continuously through electronic channels. Rapid changes in incoming and outgoing funds can make manual monitoring insufficient. Agentic AI can assist in tracking cash flow, forecasting liquidity needs, managing balances, and providing alerts when transaction patterns shift significantly. Kshetri (2025) asserts that artificial intelligence and machine learning hold substantial promise in banking risk management. This perspective is particularly relevant as treasury operations directly impact liquidity resilience and operational stability.

Table 3. Role of Agentic AI in Automating Treasury Management

Treasury Area	Role of Agentic AI	Impact on Digital Banks
Cash flow	Monitors incoming and outgoing funds	Banks can quickly assess cash positions
Liquidity	Forecasts funding needs	Reduces the risk of funding shortfalls
Operational balance	Assists in fund management	Funds can be utilized more efficiently
Early warning	Detects unusual transaction changes	Management can respond more swiftly
Funding	Provides recommendations for funding needs	Financial planning becomes more targeted

While treasury automation can enhance efficiency, the boundaries of system authority must be clearly defined. Liquidity and funding decisions directly affect bank stability and should not be entirely delegated to AI. The system can assist in data interpretation, alerting, and recommendations, but strategic decisions must remain with management, who understand the associated risks, regulations, and market conditions.

3.1.4. Summary of Research Findings

The analysis indicates that agentic AI plays a significant role in supporting financial decisions within digital banking. In customer risk profiling, the technology aids banks in recognizing risk patterns through more diverse data. In loan approval predictions, agentic AI accelerates credit feasibility analysis and enhances assessment consistency. In treasury management, the system facilitates more responsive monitoring of cash flow, liquidity, and funding needs. However, these benefits cannot be separated from implementation risks. Data bias, models lacking interpretability, information security, and insufficient human oversight can create new challenges for banks. Therefore, the use of agentic AI must be accompanied by model audits, effective data management, and clearly defined authority limits.

Table 4. Summary of Findings on the Utilization of Agentic AI in Digital Banking

Research Focus	Key Findings	Implications
Customer risk profiling	Neural scoring, feature selection, and random forest enhance credit risk assessment	Risk profiles can be more accurate and adaptive
Loan approval predictions	Ensemble learning and machine learning strengthen credit feasibility predictions	Loan processes become faster and more consistent
Treasury automation	AI aids in monitoring cash flow, liquidity, and funding needs	Treasury management becomes more responsive
Main challenges	Data bias, models lacking explainability, information security, and human oversight	AI governance needs to be strengthened

Agentic AI can enhance financial decision-making in digital banking. However, its application must be regulated through data quality, model audits, information security, decision transparency, and human oversight. Banks should view agentic AI as an analytical support tool rather than a complete replacement for analysts and decision-makers.

3.2. Discussion

The adoption of agentic AI in financial decision-making within digital banking signifies a transition from basic automation to systems capable of understanding objectives, processing data, and offering recommendations based on evolving information. Paleti (2024) identifies three essential functions of modern banks associated with agentic AI: customer risk profiling, predictive loan approvals, and automated treasury management. These functions are directly related to the quality of financial decisions, especially as banks navigate continuously changing customer data and the demand for rapid service.

In customer risk profiling, agentic AI enables banks to assess risk in a more dynamic manner. Traditional evaluations rely on established metrics such as credit history, income, employment status, collateral, and payment records. While these methods remain relevant, digital transaction patterns provide additional, rapidly changing data, including balance fluctuations, payment regularity, digital channel engagement, and cash flow. Cao (2022) emphasizes that AI in finance is linked to prediction, optimization, and the processing of large datasets. This underscores the necessity for agentic AI in risk mapping, as banks require systems that can swiftly interpret data changes. Bhatore et al. (2020) illustrate the widespread use of ensemble models, hybrid approaches, neural networks, and support vector machines (SVM) in credit scoring, predicting defaults, and fraud detection. These findings demonstrate that agentic AI can leverage advanced machine learning techniques for credit risk evaluation. However, the sophistication of models does not guarantee equitable outcomes. Banks must ensure the data used is clean, relevant, and devoid of historical biases. If outdated data contains patterns of unfair treatment, the system risks perpetuating similar biases in new decisions.

In the realm of loan approval predictions, agentic AI can streamline credit analysis while preserving the role of human analysts. Sadok et al. (2022) note that AI facilitates the use of new information sources and big data for assessing borrower eligibility. This capability is particularly advantageous for digital banks, which often face a high volume of loan applications requiring prompt responses. The system can analyze payment histories, income levels, debt ratios, cash flows, and transaction behaviors before providing initial recommendations. Support for the implementation of AI in credit predictions is echoed in various studies. Moscato et al. (2021) compare machine learning approaches for predicting credit scores, while Bao et al. (2019) integrate unsupervised and supervised algorithms in credit risk assessments. Zhu et al. (2019) utilize random forests to predict loan defaults, and Barboza et al. (2017) highlight the effectiveness of machine learning in bankruptcy predictions. Collectively, these studies suggest that predictive models can assist banks in identifying risks earlier. Nonetheless, model outputs must be carefully examined, as credit decisions have direct implications for customer access to financing.

A critical issue in loan approvals is the clarity of decision explanations. Bussmann et al. (2021) discuss the importance of explainable machine learning in credit risk management to ensure that prediction outcomes are comprehensible to decision-makers. Rudin (2019) critiques the reliance on black-box models for high-stakes decisions and advocates for interpretable models from the outset. This perspective is particularly relevant in banking, where credit decisions require justifiable rationale, especially when customer applications are denied.

In treasury management, agentic AI can assist banks in managing cash flow, liquidity, operational balances, and funding needs. Paleti (2024) identifies automated treasury management as a key application area for agentic AI within modern banking. This function is vital, as digital banks handle transactions that occur nearly continuously. Rapid changes in incoming and outgoing funds can make manual monitoring insufficient. Agentic AI can provide early alerts for shifts in transaction patterns, aid in liquidity projections, and support fund allocation. However, treasury management should not be entirely delegated to automated systems. Decisions regarding liquidity and funding directly affect bank stability. Milojević and Redzepagic (2021) argue that artificial intelligence and machine learning present significant opportunities in banking risk management, but these opportunities must be accompanied by strong oversight. Agentic AI should enhance management's ability to interpret financial conditions rather than replace strategic decisions that require consideration of regulations, market dynamics, and the bank's risk tolerance.

The literature indicates that agentic AI can strengthen financial decision-making in digital banking through faster risk analysis, more consistent loan predictions, and more responsive treasury management. Nevertheless, banks must establish robust data governance, model validation, regular audits, customer information protection, and clear authority limits for systems. Without such oversight, agentic AI could accelerate erroneous decisions and exacerbate bias risks. Therefore, the optimal role for agentic AI lies in serving as a decision-support tool that enhances the efforts of analysts, risk managers, and treasury professionals.

4. CONCLUSION

Agentic AI can significantly enhance financial decision-making in digital banking, particularly in assessing customer risk profiles, predicting loan approvals, and automating treasury management. The literature indicates that this technology allows banks to analyze transaction data, payment histories, cash flow, debt ratios, and various financial indicators more efficiently and consistently than traditional methods. In customer risk profiling, agentic AI enables banks to detect changes in financial behavior that may not be easily recognizable through conventional approaches. For loan approvals, the system can generate preliminary recommendations regarding creditworthiness based on patterns in payments, income, and transaction history. In treasury management, agentic AI aids in monitoring cash flow, managing operational balances, forecasting funding requirements, and providing early alerts for liquidity shifts. However, despite its considerable advantages, agentic AI should not function as the sole decision-maker. Financial decisions have far-reaching implications for credit access, customer data protection, service equity, and overall bank stability. Models that seem accurate can still produce flawed decisions if the data used is biased, unclean, or irrelevant.

Therefore, banks must prioritize robust data governance, conduct thorough model audits, ensure information security, clarify decision-making rationales, and maintain human oversight. The optimal role for agentic AI lies in serving as an analytical support tool that complements the work of analysts, risk managers, and treasury professionals, rather than replacing the critical judgment of experienced professionals.

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