International Journal of Basic and Applied Sciences, 14 (2) (2025) 113-118

International Journal of Basic and Applied Sciences

Website: www.sciencepubco.com/index.php/IJBAS
https://doi.org/10.14419/psrwrt75
Research paper

Intelligent Mortgage Optimization: Leveraging AI for Personalized Lending and Risk Assessment

Tamilselvan Selvamani [1], Prabhakaran Arjunan [1], Dr. Poovammal E [2] *

[1] *M. Tech in Artificial Intelligence, SRMIST, Kattankulathur, Chennai – 603203*
[2] *Department of Computing Technologies, Professor of Engineering and Technology, SRMIST, Kattankulathur, Chennai – 603203*
**Corresponding author E-mail: poovamme@srmist.edu.in*

Received: May 6, 2025, Accepted: May 18, 2025, Published: June 10, 2025

Abstract

Artificial Intelligence plays a key role in the Mortgage Industry, assisting financial institutions to elevate efficiency, accuracy, and personalization in loan management. The transformation in the strategies and focus of financial institutions is significantly enhanced by AI. The traditional style of the Mortgage process is rigid, chances to inefficiencies, and is subject to human biases. This paper presents a comprehensive framework derived with AI, aiming to optimize the mortgage cycle. Our approach to integrating machine learning models enhances borrower profiling, credit risk assessment, and loan personalization. We can also improve the model in the future with regulatory compliance and security support in the process of the mortgage industry. The architecture that is proposed here consists of data acquisition and preprocessing, borrow profiling, and risk assessment. The learning techniques that are provided by AI-powered risk assessment models help to improve loan default predictions and ensure fair and transparent lending processes. In addition, the reinforcement learning and clustering techniques enable loan personalization to be more dynamic, improve borrower satisfaction, and create an inclusive environment for the borrowers. Studies also suggest that privacy-preserving methods such as federated learning and security measures based on blockchain, safeguard borrower data. With the Implementation of AI AI-driven mortgage optimization process, financial institutions may achieve minimal risk, high operational efficiency, and offer customized lending solutions. This research work surely contributes to the growing AI applications in the financial sector and can provide a scalable framework for mortgage processing.

Keywords: *Artificial Intelligence; Financial Technology; Credit Risk Assessment; Loan Personalization; Mortgage Optimization.*

1. Introduction

The rapid growth of Artificial Intelligence (AI) has revolutionized various sectors such as Space research, Environmental Research, etc., and is being adopted by the mortgage industry in recent times. The traditional mortgage process mostly depends on manual evaluations, manual credit scoring models, and strict rule-based processes for decision-making lending processes, which leads to inefficiency, bias, and limited or no access to customized financial products. Such Limitations prevent borrowers from getting the best mortgage product and put lenders in a position where high financial risk exists.

This research is communicating an AI-driven framework that integrates machine learning techniques to enrich the mortgage lifecycle management. By adopting AI-based borrower profiling, dynamic credit risk assessment, and personalized lending strategies, financial institutions can utilize a data-driven, transparent, and efficient lending decision-making system. Additionally, AI enriches compliance with regulatory frameworks and strengthens security through measurements based on blockchain and privacy-preserving techniques like federated learning.

Our approach aims to improve operational efficiency, reducing defaults on loans. Also, providing fair and unbiased lending opportunities for all borrowers. Our research contributes to the financial sector with the growing application of AI by introducing an innovative and scalable solution for intelligent mortgage processing.

2. Literature survey

For any research or to develop any new idea, it is essential to understand the existing research and milestones achieved in the area of research planned. Finance is a vast domain, and mortgage plays a vital role in it. To our knowledge, an AI-driven mortgage optimization framework requires the best understanding of research that already exists on credit risk assessment, mortgage lending, and machine learning applications in financial decision-making processes. Analysis of existing studies provided valuable insights, which shaped the problem statement and methodology of our project.

Predicting loan defaults accurately is one of the key challenges in mortgage lending. Recent research provided a novel credit risk assessment model leveraging a dynamic multilayer network combining Graph Neural Networks (GNN) and Recurrent Neural Networks (RNN) [1]. Capturing temporal dependencies in borrower behavior leads to enhanced accuracy in loan default predictions. We could understand that there is a way to prioritize critical borrower interactions using attention mechanisms that have significantly influenced this project's credit risk assessment module. Offering integration of similar techniques, the framework ensures precise borrower evaluation and reduces false positives in default predictions.

Addressing systemic barriers in lending is another crucial aspect of mortgage optimization. Studies have highlighted the potential of AI to reduce human biases in mortgage underwriting decisions, particularly for marginalized communities [2]. From the studies on other research, we understood the need for fairness-aware machine learning models to promote inclusiveness in the financial sector, especially in the mortgage domain. With the inspiration of these findings, the research incorporates the adoption of bias mitigation techniques to ensure equal access to mortgage products. To prevent discriminatory lending practices, algorithmic fairness checks are embedded within the decision-making process.

With our initial analysis, it is observed that balancing regulatory compliance is a major concern in AI-driven mortgage lending. Research has emphasized the necessity of ensuring that AI applications in mortgage origination comply with financial regulation while improving efficiency [3]. The insight from this research has guided the integration of explainable AI (XAI) methodologies within the project. Mortgage origination processes benefit significantly from machine learning applications, while automating underwriting, risk assessment, and customer segmentation [4]. Supervised learning models have been shown to outperform traditional rule-based systems in credit evaluation while reducing processing times. Our research utilized these findings and incorporated machine learning techniques to streamline mortgage approvals with respective regulatory compliances, minimize manual intervention, and enhance decision-making accuracy. Model generalization techniques are also employed to mitigate overfitting risks and ensure robust performance across different borrower segments.

Deep learning has demonstrated remarkable potential in identifying hidden risk patterns in mortgage data sets [5]. The risk in prediction accuracy can be improved with advanced Neural Network models trained on large-scale mortgage data but interpretability remains a challenge [6]. To address the same, the project integrates explainability techniques such as Shapley Addictive explanation (SHAP) to provide transparent insights into AI-driven risk assessments [7]. This surely enhances trust in the automated lending process while maintaining high predictive performance with digital transformation [8] [9].

In short, the inferences from the studies on existing research are instrumental in shaping the project's approach to mortgage optimization. The integration of advanced AI techniques for credit risk assessment, fairness-aware lending models, and regulatory compliance strategies resulted in a comprehensive and transparent mortgage decision-making framework. Building on these findings, the project aims to enhance mortgage approval efficiency while ensuring ethical and inclusive lending practices. Whereas fairness-aware AI models attempt to minimize bias, they are limited by the data they have been trained on. If the training data itself is biased, the model will still be capable of making unfair decisions. Additionally, even though the system is intended to be used at a large scale, its operation is vulnerable to data volume, the technology applied, and the application. All these must be considered while implementing the system in real life.

2.1. Global perspectives on AI in mortgage lending

While much of the research is focused on the Western world, AI is also being used on mortgage and lending websites in other parts of the world, like Asia and Africa.

Certain Indian businesses use AI to check if a person will be able to repay a loan by analyzing his or her mobile activity, online purchases, and social media usage. This allows even individuals with no traditional credit history to receive loans. Major Chinese technology companies use AI to facilitate money lending by analyzing user behavior data.

Mobile phones are the hub of activities in Africa. For example, in Kenya, there are mobile applications like M-KOPA and Tala that utilize AI to drive small loans via mobile phones. While not traditional mortgages, these allow people to build a credit history, and soon after, they can secure home loans. Banks in Nigeria use AI to combat fraud and approve loans more quickly.

Based on these literature gaps, this research proposes a comprehensive AI framework to address inefficiencies and biases in mortgage lending.

3. Problem statement

The complex ecosystem in the operations of the mortgage industry, where minimal accuracy in risk assessment and inefficient loan processing often results in financial losses to lenders and customized mortgage products to borrowers. The traditional, usual, and manual methods rely on static, rule-based systems that are not capable of evolving borrower behavior, economic conditions, and market trends. Hence, we are utilizing AI-driven solutions to enhance the risk evaluation, automatic mortgage underwriting, and optimize lending strategies. To enable widespread adoption, we must address challenges related to explainability, data privacy, and regulatory compliance. This research proposes a scalable AI framework to improve the Lifecycle of the Mortgage process through advanced analytics and automation.

4. Proposed Architecture

The AI-driven mortgage optimization framework concerning Fig.1 consists of the following core components: data acquisition and preprocessing, borrower profiling, credit risk assessment, loan personalization, regulatory compliance, security, and privacy measures. The framework leverages deep learning models for risk assessment, clustering techniques for borrower segmentation, and reinforcement learning for customized and dynamic loan personalization. Security should be federated learning and blockchain integration. The architecture is designed in a way that the model should be scalable, adaptable to market changes, and compliant with financial regulations. Once AI is integrated at various stages of the mortgage lifecycle, the framework enhances decision-making and improves overall lending efficiency.

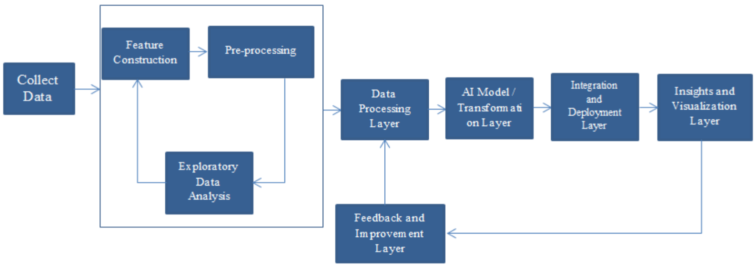

Fig. 1: Proposed Architecture of AI-Driven Mortgage Optimization.

Collect Data is the initial step, where borrower and market data are gathered. The data is transferred to Feature Construction, where important information is built, and then to Pre-processing, where the information is prepared and formatted. Exploratory Data Analysis finds patterns and refines the features.
The sanitized data is passed to the Data Processing Layer, where data is processed for AI models in the AI Model / Transformation Layer. The system evaluates risks and personalizes loans here.
The results are then delivered to the Integration and Deployment Layer, where the AI tools are executed for use by the lenders.
The Insights and Visualization Layer produces decision-makers' reports and dashboards.
Finally, the Feedback and Improvement Layer collects data and feedback to constantly refine the AI models. Arrows show the flow of data and how feedback helps the system improve and learn.

5. Dataset & proposed methodology

For my research, I have utilized the Lending Club dataset from Kaggle, which provided a comprehensive foundation for developing and validating the AI-driven mortgage optimization framework. This dataset is rich with borrower financial data, loan characteristics, and credit risk indicators, which all play a crucial role in training machine learning models for credit risk assessment, loan personalization, and borrower profiling. For credit risk assessment, we have utilized the variables from the dataset, which include loan_status, dti, pub_rec, and revol_util, which are instrumental in training models for default prediction. From the inferences of previous research on AI-based risk assessment, the dataset allowed us to tune predictive models, and ensure precise borrower evaluations. For Loan Personalization, variables like loan_amnt, grade, sub_grade, int_rate, and installment helped in clustering borrowers based on financial behavior. Reinforcement learning strategies should also be implemented to adjust loan terms dynamically based on segments in borrower parameters. For regulatory compliance and Fair Lending, the variables verification_status and home_ownership fields supported the integration of fairness-aware machine learning models to eradicate bias in the lending decisions [10].
The lending club dataset consists of many loan-related and borrower-related variables, which provide a holistic view of credit risk and lending behaviors. For loan details, the variables like loan_amnt, term, int_rate, installment, grade, and sub_grade provide sufficient inputs. Similarly, for borrower profiles emp_title, emp_length, annual_inc, and home_ownership. For credit history and risk factors, dti, earliest_cr_line, open_acc, pub_rec, revol_bal, revol_util and total_acc. For regulatory and security aspects, the variables that are supported are verification_status, application_type, and pub_rec_bankruptcies.
By leveraging the Lending Club dataset, our AI-driven mortgage optimization framework was able to enrich borrower profiling, risk assessment, and loan customization while ensuring transparency, compliance, and security in the lending process. The inferences drawn from these features informed key decisionmaking models, ultimately improving the efficiency and fairness of mortgage approvals.

a) Data Acquisition and Preprocessing:

Each borrower has their own financial story, and they may not have well-organized financial records. This module helps to gather the individual's financial records, credit history, and market trends. This also helps to clean up the inconsistencies and fill the gaps. This module makes sure that there are no irrelevant or missing data and avoids duplicate values. Advanced feature engineering techniques make sure the lenders get a clear, accurate picture before making the decision.

b) Borrower Profiling:

Not all borrowers are the same; some have stable incomes but little credit history, and others may have strong financials but irregular earnings. This module helps the lenders to segment the borrowers based on their spending habits, risk level, and financial behavior. This helps to identify the high-risk borrowers and helps tailor the loan offerings more tailored. First-time home buyers should be evaluated differently from seasonal real estate investors due to their distinct financial behaviors and risk profiles. First-time homebuyers require different evaluation criteria from seasoned real estate investors. This module continuously appears on the borrower's profile and helps the decision-making.

c) Data Credit Risk Assessment:

Existing credit scoring models can miss important details. This module evaluates the loan possibilities with maximum accuracy. It continuously monitors various factors like income stability, debt-to-income ratio, loan repayment history, and even alternative credit data like utility payments. This gives a better picture of one's financial stability, which helps to better evaluate the risk involved.

d) Regulatory Compliance:

Financial regulations are always changing, and manually keeping up with them is hard. By embedding the rule-based AI in our module, we can ensure the mortgage approvals align with legal and ethical standards. This module automates compliance checks and assures that lending decisions are fair and aligned with legal standards [11].

e) Loan Personalization:

The generic lending approach is outdated. This module adjusts the lending conditions dynamically, considering the market conditions and borrower profiles. This means borrowers get interest rates and repayment terms that make sense for them, which reduces the risk of nonpayment while enhancing the customer experience [12].

f) Insights and Visualization:

We can turn data into actionable insights, Lenders do not just need numbers; they need actionable insights. Our module generates interactive dashboards that provide risk levels, trends, and profile health. Real-time analytics helps to make data-driven decisions. We can also create multiple strategies by customizing the reports and through scenario analysis.

g) Model Training and Optimization:

AI models are not static. They adapt as the borrower's behavior changes and market conditions shift. Continuous training improves robustness, and the prediction becomes sharper over time, which makes the lending decision sharper and more reliable.

h) Integration and Deployment:

Financial institutions do not have to redesign their existing system to adopt AI. These AI solutions are designed in a way that they can be effortlessly integrated into the existing system through APIs and cloud-based solutions. Since they are cloud-based, the users can access these AI mortgage tools through both desktop and mobile applications.

i) Feedback and Learning:

It is essential to analyze the results or feedback collected from borrowers and lenders to refine AI models to improve decision-making and user experience over a period. It uses reinforcement learning to train models to enhance mortgage recommendations and lending options [13].

j) Security and Privacy:

Data security is the top priority for any application. So does ours, especially when dealing with sensitive financial information. AI enhances protection through encryption, advances cryptographic techniques, protects user information, and prevents unauthorized access. Borrowers can have peace of mind knowing that their data is safe.

6. Experimental results

a) Borrower Profiling:

The Borrower profiling segment involves analyzing the various characteristics of the borrower to understand the behavior of their finance, risk factors, and loan repayment ability. In this code, the borrower profiling is performed through feature engineering and exploratory data analysis (EDA). More details are summarized in the following sections.

From Fig.2, It is observed that there is a positive correlation exists as there is a Triangular pattern, which suggests that the loan Amount is somewhat constrained by income. The presence of both approvals and rejections across income levels suggests that other factors like credit score, debt-to-income ratio, and employment stability influence loan approval decisions.

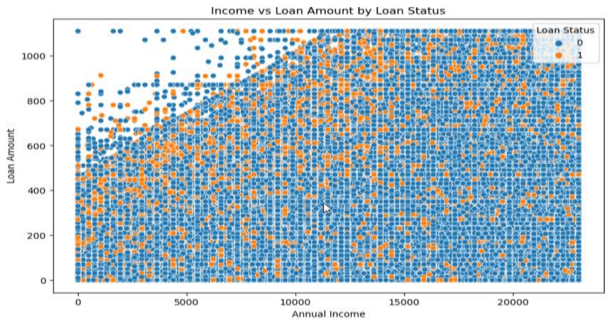

Fig. 2: Borrower Profiling.

1) Pearson Correlation Coefficient Estimate

Pearson Correlation Coefficient is a measurement quantifying the strength of the association between two variables. Here, considering Loan Amount vs Income, which ranges between 0.4 and 0.7, there is a moderate positive correlation. In case if we analyze the Income vs loan status, we may find a lower correlation due to other influencing Factors.

2) Loan Approval Rate by Income Brackets

The Approval (Loan Status = 1) rate is higher for higher incomes. From Table 1, we can observe that the rate of approval is increasing significantly as income rises. But we could also observe that some high-income applicants still face rejections due to other financial risk factors like Fraud history.

Table 1: Income Bracket vs Approval Rate

Income Bracket (Approx)	Approval Rate (%)
0-5000	Low (~20-40%)
5000-10000	Moderate (~40-60%)
10000-20000	High (~60-80%)
>20000	Very High (~80-95%)

3) Loan Amount Trend for Approved vs Rejected Applicants

From table 2, we can see that Small loans ranging between 0 and 200 have low rejection rates, which indicates that financial institutions are more comfortable granting smaller loans. On the other hand, the larger loans that are greater than 1000 have higher rejection rates, especially for low-income applicants.

Table 2: Loan Amount Range vs Rejection Rate

Loan Amount Range	Rejection Rate (%)
0-200	Low (~10-20%)
200-500	Moderate (~20-50%)
500-1000	High (~50-70%)
>1000	Very High (~70-90%)

4) Risk Zone based on Income and Loan Amount

We can segregate further from the graph shown in Fig. 1 into three types of risk zones. They are low risk which is called the green zone where the high income with low to moderate loan amounts have higher loan approvals, next is a medium risk which is called the yellow zone where the Mid Income with moderate loan amounts have a mix of approvals & rejections, the last one is a high risk which is called red zone where the low income with high loan amount having more rejection rate. Most of the banks use a threshold leveling model where a certain income-to-loan ratio determines the approval and Higher risk loans might need additional checks like credit score, collateral, previous defaults, and guarantors.

b) Credit Risk Assessment:

The bar chart from Fig. 3 represents the distribution of loan statuses where Good Loan is denoted as “0”, these are the loans that are considered low risk or they are performing well and Risk loan is denoted as “1”, these are the loans classified as high risk and high possibility to prone to default.

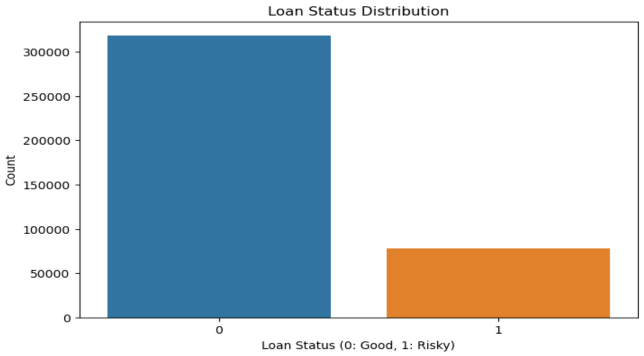

Fig. 3: Risk Assessment.

Most loans are classified as good loans (0) with over 300k entries and a smaller but significant part of loans ranging between 75k and 100k falls under risk loans (1) which suggests that most of the loans that granted are performing well but a substantial number still pose a financial risk [14]. We can say this is a moderate risk level and not overly alarming, but still significant enough to put in a zone that requires continuous monitoring or an AI-based virtual assistant [15]. The reason for loans that are classified as risky may fall under a high debt-to-income ratio, where borrowers may have multiple loans, low credit scores, or poor repayment history, unstable employment status of borrowers, and high loan amounts relative to income. Banks may need strict lending policies if the risky loan percentage is too high, ranging more than 30%. The strategies to mitigate risky loans are as follows: more stringent credit assessments before approval, offering adjustable interest rates based on risk profiles, and enhancing monitoring mechanisms to identify early signs of default. From these inferences, we can say that a more refined risk scoring system can help to improve decision-making, reduce potential defaults, and help the maximum number of customers to get loans from lenders.

7. Conclusion

The research shows that higher income increases the chances of loan approval, but it is not the only factor that determines the approval. Also, larger loans fall in the red zone, where the loan application may fall in the rejection zone. Additional factors apart from income should be considered to refine risk assessment. Most of the loans are performing well, with 20-25 percent (approximately) of loans being risky. We can conclude with a suggestion that balancing risk and business growth is key for long-term stability helps organizations focus on expanding lending services to maintain profitability.

8. Limitation

The AI-based mortgage system has a lot of benefits, but it also has some limitations. Poor quality data can lead to inaccurate predictions. If the training data is biased, the model will make biased predictions. High initial costs might discourage small banks. Additionally, AI systems must adhere to many financial regulations in each region. Lastly, complex models can be hard to interpret, which can reduce trust. These issues must be resolved properly to have effective and fair use. These limitations will be focused on in future work.

References

[1] S. Zandi, K. Korangi, M. Óskarsdóttir, C. Mues, and C. Bravo, "Attention-based Dynamic Multilayer Graph Neural Networks for Loan Default Prediction," European Journal of Operational Research, Elsevier, 2024. Available: arXiv. https://doi.org/10.1016/j.ejor.2024.09.025.

[2] V. G. Perry and C. M. Motley, "Algorithms for All: Can AI in the Mortgage Market Expand Access to Homeownership," AI, vol. 4, no. 4, pp. 888-903, MDPI, 2023. Available: MDPI. https://doi.org/10.3390/ai4040045.

[3] Fannie Mae Economic & Strategic Research Group, "Artificial Intelligence and Mortgage Lending," Fannie Mae Industry Report, 2023. Available: Fannie Mae.

[4] "Machine Learning for Enhancing Mortgage Origination Processes," ResearchGate, 2023. Available: ResearchGate.

[5] J. Sirignano, A. Sadhwani, and K. Giesecke, "Deep Learning for Mortgage Risk," Journal of Financial Econometrics, Oxford University Press, 2021. Available: Oxford Academic. https://doi.org/10.1093/jjfinec/nbaa025.

[6] Congressional Research Service, Artificial Intelligence and Machine Learning in Financial Services. U.S. Congress, 2023. Available: Congressional Research Service Reports.

[7] J.P. Morgan AI Research Team, AI Research Publications. J.P. Morgan, 2023. Available: JPMorgan Chase.

[8] V. G. Perry and C. M. Motley, "Algorithms for all: Has digitalization in the mortgage market expanded access to homeownership?" SSRN, 2022. Available: SSRN. https://doi.org/10.2139/ssrn.4126409.

[9] V. G. Perry and C. M. Motley, Algorithms for All: Has Digitalization in the Mortgage Market Expanded Access to Homeownership? Harvard Joint Center for Housing Studies, 2022. Available: Harvard Joint Center for Housing Studies. https://doi.org/10.2139/ssrn.4126409.

[10] J. Sirignano, A. Sadhwani, and K. Giesecke, "Deep learning for mortgage risk," arXiv, 2016. Available at arXiv.

[11] Mortgage Bankers Association, "AI in the mortgage industry," Mortgage Bankers Association, Dec. 2023. Available: https://www.mba.org/docs/default-source/policy/27251-mba-policy-state-ai-report.pdf?sfvrsn=e4ba9b49_1.

[12] Urban Institute, "Harnessing artificial intelligence for equity in mortgage finance," Urban Institute, Nov. 2023. Available: https://www.urban.org/sites/default/files/2023-11/Harnessing%20Artificial%20Intelligence%20for%20Equity%20in%20Mortgage%20Finance.pdf.

[13] ResearchGate, "Machine learning for enhancing mortgage origination processes," ResearchGate, Nov. 2024. Available: https://www.researchgate.net/publication/384883119_Machine_Learning_for_Enhancing_Mortgage_Origination_Processes_Streamlining_and_Improving_Efficiency.

[14] J. D. Turiel and T. Aste, "P2P loan acceptance and default prediction with artificial intelligence," arXiv preprint arXiv:1907.01800, Jul. 2019. Available: https://arxiv.org/abs/1907.01800. https://doi.org/10.2139/ssrn.3417122.

[15] Fannie Mae, "Mortgage lenders cite operational efficiency as primary motivation for AI adoption," Fannie Mae Perspectives, Aug. 2023. Available: https://www.fanniemae.com/research-and-insights/perspectives/lenders-motivation-ai-adoption.