Paradigm

A REAL ESTATE DEVELOPMENT RISK RATING MODEL USING MACHINE LEARNING AND MULTIDIMENSIONAL DATA (RED RM)

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ABSTRACT

The real estate sector is a cornerstone of economic development, significantly contributing to GDP and employment. For financial institutions, assessing the creditworthiness of developers and buyers is crucial to mitigate credit risks and maintain financial stability. In this context, the purpose of this study is to propose a model for real estate development rating to enhance the decision-making process. To achieve this, we combined existing data and collected ones with insights from experts, along with a machine learning perspective, to create a multidimensional model, with its features and process, which takes into account companies, projects, and market data. For the proposed grid, the selected features include companies' financial data, historical behavior, project ratios, location with proximity to amenities, mobility and accessibility, macro market data and other influencing ones. Applied to 653 different cases in Morocco between 2016 and 2025, the rating is based on the XGBoost probability of default and confronted to the effective default to be used by banks and developers.

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1. Introduction

The real estate market is an essential component of any economy, reflecting and influencing the overall economic health of a region. The 2007 crisis has effectively more brutally affected the USA than the whole financial world. It has first impacted the financial sector, then real estate before affecting the other sectors (Jouahri & de Bank Al-Maghrib, 2009). It started with risky lending practices in the U.S. housing market, where banks issued loans to borrowers who couldn't afford them (Subprime Mortgage Market Boom). As housing prices fell, many defaulted, causing massive losses for financial institutions worldwide and leading to a global economic downturn. In response, governments introduced stricter regulations and financial reforms to prevent similar crises in the future. The real estate market therefore has a huge impact and is impacted by the macroeconomic context.

Morocco was selected as a test case due to the diversity of project types, and the maturity of the banking system, even though the data availability is still an issue. Its transitional economy and rapid urbanization offer a fertile ground to test risk models with spatial, macroeconomic, and institutional dynamics. While the model was calibrated using Moroccan data, its structure is generalizable. With appropriate adaptation, the RED RM framework can be applied to other emerging or developed markets.

As a significant driver of economic growth, this sector not only contributes to job creation and infrastructure development but also impacts consumer confidence and spending. Understanding the dynamics of the real estate market is vital for investors seeking to make informed decisions and for policymakers aiming to create effective economic strategies (Horvátová, 2024). In this context, it's essential to carry out in depth studies of the macroeconomic context and the specific data related to real estate, while studying the market in a specific country or city. For instance, Morocco is confronted with distinct economic challenges, characterized by rapid population growth and rising urbanization. These factors are driving up the demand for infrastructure and housing, thereby fostering growth in the real estate sector. To follow these trends and acknowledge them, the government makes some crucial real estate data available for stakeholders to evaluate the dynamic of the sector. Unfortunately, actual stakeholders do not collaborate to reflect the real picture of the market or provide detailed data for future customers, developers or banks to assess the market.

These relationships emphasize the importance of examining the factors that drive developer behavior, particularly in the context of securing financing. In recent years, the rise of technological advancements in GIS (Geographical Information Systems), prop-tech (property technology) and fintech (financial technology) has begun to transform traditional real estate and lending practices (Naeem et al., 2023). Innovations such as big data analytics and artificial intelligence have equipped, for example developers and lenders, with tools to predict asset prices and evaluate them (Chen et al., 2023) (Surgelas et al., 2024). It allows also for risks to assessed more accurately and financing processes to be streamlined. These advancements present opportunities for real estate developers to navigate market fluctuations more effectively, but also require a deeper understanding of how these technologies impact borrower behavior and repayment.

Substantial research has been conducted mainly on personal loans for home purchases and consumer finance (Anand et al., 2022; Zhang et al., 2023) but also for company loans (Dai et al., 2021; Nejjar et al., 2024); nevertheless, there remains a gap in studies specifically addressing financial behaviors of real estate developers and the impact of market and project factors.

This study seeks to address this gap by developing a rating model to evaluate real estate projects based on developer, market, and project-specific characteristics. This model will be tested using data from a Moroccan bank focused on residential projects. By comparing the model's results with expert evaluations, we aim to validate its applicability and offer a framework that can be beneficial to both developers and lenders.

The insights from this research are expected to deepen understanding of the real estate development landscape, supporting more informed decision-making among practitioners and policymakers. Additionally, these findings have the potential to refine financing strategies for real estate projects, contributing to the sustainable growth of this vital sector within the economy. This research allows lenders to assess financing requests for real estate development without relying solely on traditional methods. The study confirms that the location and proximity of commodities are crucial factors for success, as emphasized by experts. We will first present the background to the study giving some definitions and guidelines, and then go on to the literature review. This will be followed by a grid along with its features and weights, based on the case study of Morocco.

Inspired by domain expert knowledge and machine learning, this work presents a novel multidimensional scoring model incorporating developer, project, and market-level variables. Unlike current models that concentrate on borrower-level or property-level characteristics alone, our method embeds ESG metrics, spatial qualities, and real finance data in a holistic framework suited to developing markets like Morocco.

Morocco's transitory real estate sector, strong finance structure, and data availability create a convincing test bed. The model's design is generalizable even if its parameters are local-specific.

2. Background

2.1. European Banking Authority Guidelines

The European Banking Authority (EBA) report distinguishes between different types of businesses in its modeling:

- micro and small businesses,
- medium and large companies,
- commercial real estate (CRE) promotions,

In the EBA guidelines on loan origin and monitoring, criteria for assessing the solvency of borrowers are provided for both small and medium-sized enterprises (SMEs) as well as large enterprises (GEs). However, additional criteria are required for evaluating the solvency of commercial real estate (CRE) transactions, beyond those applicable to SMEs and GEs.

Furthermore, as of 29 May 2020, banks must assess credit applicants for ESG risk exposure, following the EBA Guidelines (Barbaglia et al., 2023).

2.2. Basel Accords

Basel Accords is a series of international banking regulations developed by the Basel Committee on Banking Supervision (BCBS). Their objective is to enhance the stability and resilience of the global financial system by establishing standardized guidelines for risk management and capital adequacy among banks. From the first version in 1988 to the latest guidelines of Basel III in 2017 and their recent reforms, after the 2008 financial crisis, stringent capital

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requirements, leverage ratios, and liquidity standards are in place to strengthen the banking sector's ability to absorb shocks (Finalising Basel III - In Brief, 2017).

Market rating refers to the macro-environmental and spatial risk level associated with the geographic location of a development project, capturing investment appeal, historical volatility, and market absorption capacity.

2.3. Bank Al Maghreb regulation

Bank Al-Maghrib, Morocco's central bank, plays a crucial role in maintaining the stability and soundness of the country's financial system. Its key responsibilities include shaping and implementing monetary policy, supervising credit institutions, and managing foreign exchange reserves. In terms of credit risk management, the bank has put in place a solid regulatory framework that aligns with international standards, such as the Basel Accords and the guidelines set out by the EBA. These efforts are aimed at strengthening the resilience of Moroccan banks by ensuring they can withstand potential credit risks and maintain adequate capital reserves. Through its commitment to rigorous risk management practices and a proactive regulatory approach, Bank Al-Maghrib not only enhances confidence in the financial sector but also supports long-term economic growth and stability, (Bank Al-Maghrib, 2024)

In this study, “market rating” refers to an integrated assessment of the investment environment and systemic exposure at the geographic and macroeconomic levels. It reflects both the investment attractiveness of a location and the systemic risks associated with the broader real estate and economic context.

2.4. Real estate development risk assessment and rating – use of GIS and AI focus

Recent studies on risk assessment and decision-making in real estate emphasize a variety of innovative methodologies to address the complexities of credit risk management and property valuation. In our previous studies Berrada et al. (2022) and then Rhzioual Berrada et al. (2024), we introduce a machine learning-based framework concluding that algorithms such as Random Forest and XGBoost deliver good results for forecasting corporate loan defaults. Our approach leverages financial ratios while addressing data imbalance through oversampling techniques like SMOTE. In another contribution, Lausberg and Krieger (2021) explore decision support systems (DSS) that incorporate spatial data for enhanced real estate investment strategies. Locurcio et al. (2021) propose a synthetic risk index based on Multi-Criteria Decision Analysis (MCDA) to evaluate real estate credit risks while aligning with Basel III standards. Lastly, Siddiqi (2017) focuses on developing advanced credit risk scorecards for individuals using logistic regression, offering valuable tools for financial risk management in the real estate sector. Collectively, these studies, and others like Qin et al. (2021), Anelli and Tajani (2023) and Xu et al. (2024) underline the growing reliance on algorithmic models and multidimensional analyses to address challenges such as data uncertainty, subjective evaluations, and evolving market dynamics. The following Table 1 presents them along with their employed models or methods.

Table 1

Real estate risk assessment and scoring/rating

Article	Employed models / methods
Rhzioual Berrada et al. (2024)	Classification algorithms, oversampling, evaluation metrics comparison
Chen et al. (2023)	Decision support system, optimization techniques, GIS
Lausberg and Krieger (2021)	Risk Scoring Rules Framework
Locurcio et al. (2021)	Multi-Criteria Decision Analysis, Integration of objective financial variables and subjective expert judgments, Basel III methodologies
Hellström Ängerud (2017)	Analysis of Credit Assessment methodologies, evaluation of financial ratios and repayment ability Risk modeling techniques for bond market funding versus traditional bank loans.
Siddiqi (2017)	Statistical and machine learning techniques, logistic regression, data cleaning and features selection

Source: own study.

2.5. Real estate valuation – variables focus

The reviewed literature on real estate valuation and risk assessment highlights several critical variables influencing property value and risk modeling:

- Macroeconomic Indicators: factors like interest rates, inflation, GDP, and systemic risks are emphasized by Barmeier et al. (2024) and Mooya (2016), reflecting their importance in market-driven valuation frameworks.
- Property Characteristics: variables such as size, age, condition, and type of property are consistently highlighted in Khandaskar et al. (2023) for their predictive power in pricing models and portfolio simulations.

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- Spatial and Geographic Data: the integration of GIS, as discussed by Mete et al. (2022) and Droj et al. (2024), underscores the role of location, proximity to amenities, and urban planning in property evaluations.
- Socioeconomic Factors: neighborhood attributes, demographic trends, and economic stability are vital, as outlined in Renigier-Biłozor and Chmielewska (2019), for creating comprehensive valuation frameworks.
- Market Dynamics: historical price trends, demand-supply balance, and market cycles, as discussed by Cupal (2014) and Mooya (2016), remain central to understanding valuation volatility and risk.
- Technological Tools: advanced methodologies, including machine learning (Khandaskar et al., 2023) and 3D modeling through BIM and GIS (Mete et al., 2022), have enhanced precision and predictive capabilities in valuation models.

Moreover, after the Covid 19 crisis, despite an initial decrease in demand, many families increasingly sought new property features like balconies and green spaces due to changes in lifestyle priorities during the pandemic (Ababsa, 2024).

In another perspective, Zanin (2022) analyzes the influence of Environmental, Social, and Governance (ESG) scores on corporate credit ratings in sectors such as manufacturing, mining, wholesale trade, and real estate. Credit ratings from S&P and Fitch were used alongside Refinitiv ESG pillar scores to measure sustainability performance.

3. Real Estate Development Rating Model, Process and Grid

3.1. Methodology

To develop an optimal rating model for real estate development financing requests, a systematic and multi-phased approach was adopted. This methodology comprises five primary stages: literature review, expert workshops, variable identification, gap analysis and then model validation and performance evaluation.

3.1.1. Literature Review

A comprehensive literature review was conducted to identify key studies and advancements in the field over the past decade. The review process was structured into two phases:

- General Loan Default Prediction: the initial phase involved the examination of foundational studies related to loan default prediction across various domains, providing insights into existing models, methodologies, and predictive factors.
- Real Estate Development-Specific Analysis: in the second phase, a focused review was conducted on loan default prediction specific to real estate developers. A targeted search was performed to identify a subset of articles that evaluated the unique risk factors associated with real estate development projects.

This systematic review provided a solid theoretical foundation, enabling the identification of prevailing trends, challenges, and gaps in current rating models.

3.1.2. Expert Workshops

To enhance the scientific robustness of the traditional rating approach, a series of expert workshops were conducted. These workshops involved industry professionals and financial analysts. The objectives of these workshops were to:

- Validate the findings from the literature review.
- Bridge the gap between theoretical models and practical applications.
- Refine the criteria and weighting mechanisms for assessing real estate development financing.

Through these collaborative sessions, the team of 10 contributors was able to align theoretical knowledge with industry expertise, ensuring the practical applicability of the proposed rating model.

3.1.3. Variable Identification and Selection

Following the literature review and expert consultations, the critical variables required for evaluating and scaling real estate development projects were identified. A comprehensive list of potential variables, both available and requested ones, was identified in the existing rating models. Traditional rating systems were found to inadequately address the specific needs of real estate developers.

Addressing this gap, the proposed rating model incorporates a balanced set of variables tailored to the nuanced requirements of SMEs in the real estate sector.

3.1.4. Model Validation and Performance Evaluation

To ensure the effectiveness and reliability of the proposed rating model, a comprehensive validation framework was established. This phase involved data driven validation. The model was tested using historical loan performance data from various real estate projects, comparing predicted default probabilities with actual outcomes. Statistical measures, such as accuracy, precision, recall, and the F1-score, were utilized to assess the model's predictive power.

3.2. Real Estate Development Rating Model (RED RM)

Traditionally, the approach begins with an analysis of the counterparty, specifically the real estate developer and its shareholders. The evaluation starts by assessing the developer's experience with previous projects, reviewing financial statements, and examining historical relationships, especially if the developer is involved in multiple projects. In cases where a Special Purpose Vehicle (SPV) is involved, the other companies linked to the shareholders are evaluated, considering qualitative indicators such as management quality and reputation.

Following this, technical and financial evaluation of the project is conducted to assess its consistency, feasibility, and attractiveness. Various ratios are calculated to determine the project's ability to meet debt obligations, as well as its sales potential. Other qualitative aspects, such as architectural quality and environmental compatibility, are also considered.

It is crucial to note that, even if the shareholder's credentials are exceptional and the project is well-designed, the market in which the project is developed must support the project. Otherwise, there may be no sales, leading to an inability to repay debt. This highlights the importance of evaluating the macroeconomic conditions at a specific point in time, as well as the changing environment surrounding the project.

The model we designed incorporates these three major components (the company, the project and the market), including various variables, as illustrated in Figure 1. For the company, it included data concerning the real estate company and its shareholders (financial statement ratios, historical behavior, management quality...). According to the project, data related to the project's financial ratios, architecture quality, operation, marketing and sales quality are considered along with other data. For the market, the considered data is related to the macro dynamic of the market and the micro environment of the project. The RED RM combines all these data and others.

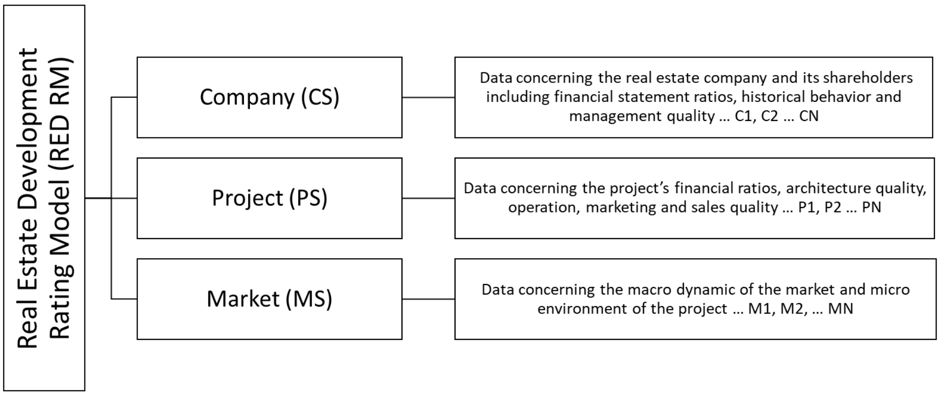

Fig. 1. Real Estate Development Rating Model Data (RED RM). *Source*: own study.

3.3. Rating Process

After drawing up the conception of the rating model and before presenting the detailed grid, we present the process. The first stage is data collection, which involves gathering information from diverse sources. This includes existing datasets, web scraping tools to retrieve online data, manual collection efforts for unavailable information, and spatial data related to nearby amenities, infrastructure, and geographic features. The aim is to compile a rich and multidimensional dataset that captures the full spectrum of factors influencing market dynamics.

Next, the collected data undergoes data preparation, where it is cleaned, organized, and enriched. During this phase, financial metrics, such as ratios and indices are calculated, while spatial data is analyzed to provide insights into location-specific attributes. This step ensures that the data is ready for deeper analysis, free from inconsistencies, and aligned with the objectives of the study.

Following preparation, the data selection phase is carried out. In conjunction with previous studies, specifically those related to real estate valuation, the selection of features is completed manually. Then within the testing phase, XGBoost is used to assign a score to each loan request, seeing as how this algorithm performs well as concluded in our previous work (Rhzioual Berrada et al., 2024). This stage involves a combination of expert judgment and machine learning techniques to identify the most important features influencing property values and market performance. The dual approach ensures that both domain knowledge and data-driven insights guide the selection process, resulting in a robust feature set.

As a reminder, Random Forest is a method of ensemble learning combining numerous trees utilizing bagging to reduce variance and improve generalization based on decision trees. It appropriately controls missing data and variable relevance. XGBoost (Extreme Gradient Boosting) generates one additive model after another, aiming to reduce the loss function. It offers parallel processing for economy and regularity, and helps to prevent overfitting. Both models perform well in handling diverse aspects, much as in real estate data.

Once the key features are identified, they are standardized through data encoding. Each feature is categorized into three classes to simplify interpretation and enhance model performance. This step makes the data more consistent and ready for analysis while retaining its essential variability and relevance.

Finally, the processed data is used for rating the company, the project, and the broader market. This step integrates all previous phases to compute a global score, offering a holistic assessment that combines financial performance, project viability, and market attractiveness. This scoring system provides a clear and actionable framework for stakeholders, whether they are investors, developers, or policymakers, enabling them to make informed and strategic decisions.

This structured process, summarized in Figure 2, ensures that the evaluation is not only data-driven but also enriched by expert insights, making it adaptable to various market contexts and challenges. The following process sets out the different steps leading to the rating of each record.

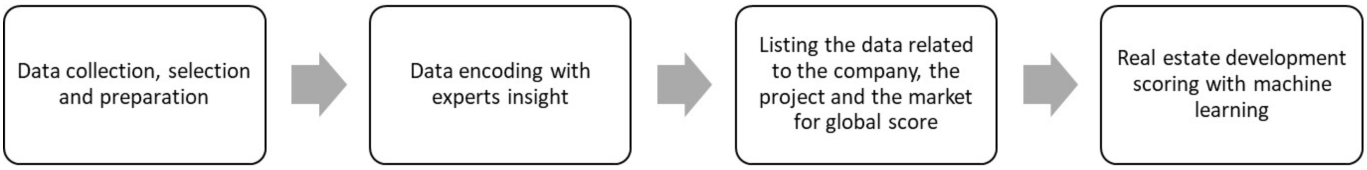

Fig. 2. Real Estate Development Rating Process. *Source*: own study.

The XGBoost, Random Forest, and Logistic Regression models were selected due to the fact that they have well-documented performance in credit risk prediction. These methods balance the handling of non-linear correlations and feature interactions (XGBoost and RF), interpretability (Logistic Regression), and accuracy. XGBoost in particular is well-known for its computational efficiency and regularizing powers, which make it appropriate for handling challenging datasets typical of real estate financing environments.

Moreover, the predicted probability of project failure is estimated over a 3-year horizon, reflecting typical development cycles in the region.

3.4. RED RM Grid and formula

Before presenting the proposed rating grid based on expert knowledge, it is essential to clarify that this study assumes that certain macroeconomic variables should only be considered if the evaluated financing requests differ in terms of time and location. These variables can lead to an upgrade or downgrade of the overall project score. Accordingly, the macroeconomic context will be assessed based on the following variables:

– Economic Growth (GDP Growth).
– Interest Rates.
– Inflation.
– Unemployment Rate.
– Demographic Trends.
– Taxation and Government Incentives.
– Political and Legal Stability.
– Ease of Doing Business and Investment Climate.

However, if the study is conducted within the same global context and timeframe, these factors will not be considered, and a neutral impact will be assumed.

Furthermore, Environmental, Social, and Governance (ESG) factors have emerged as critical evaluation criteria in real estate financing (Zanin, 2022). Prior to obtaining a building permit or a financing loan, real estate companies are required to conduct specific assessments to evaluate the ESG impact of their projects. Investors and financial institutions increasingly prioritize sustainability and responsible investment practices. ESG considerations provide a framework to assess the long-term viability and risk profile of projects, ensuring that environmental impact, social inclusion, and ethical governance are effectively managed. In this context, the Equator Principles (EPs) serve as a globally recognized risk management framework, helping financial institutions identify and address environmental and social risks in project financing. Established in 2003 and based on the International Finance Corporation (IFC) Performance Standards, the EPs ensure that large-scale real estate developments comply with rigorous environmental and social standards, including community engagement, biodiversity protection, and climate risk assessment. Compliance with these principles enables real estate developers to attract responsible investors, mitigate regulatory risks, and enhance their market reputation, ultimately fostering more sustainable urban development. As such, ESG factors are incorporated into the project scoring process.

The proposed scoring methodology for real estate development projects integrates multiple criteria, including the financial performance of the company, project components, market trends, and accessibility to essential amenities. This multi-dimensional scoring system evaluates projects from the perspectives of real estate investors, developers, and financial institutions, facilitating informed decision-making and enhanced risk management.

The primary objective is to generate an overall score that reflects not only the intrinsic characteristics of the project but also the financial health of the developer and the project's feasibility within its market context.

By leveraging business insights and a thorough literature review, the proposed rating model aims to minimize real estate financing risks, optimize portfolio management, and enhance the decision-making process.

Table 2 presents the proposed features of the rating grid, which has been refined through extensive testing and expert validation to ensure its relevance and effectiveness. This score can be fine-tuned using only the most important features for XGBoost.

Table 2

RED RM Grid features

	Id	Features	Description
Company Score (CS)	C1	Inventory/Revenue	The company's inventory in relation to its revenue
	C2	Net Cash/Total Assets	The financial stability of the company (liquidity ratio)
	C3	Net Profit/Revenue	Net profit margins of the company
	C4	Financial Debt/(Equity + Loans)	Reliance on external financing (leverage ratio)
	C5	Number of Completed Projects	The track record in project delivery and sales
	C6	Management Structure Quality	The experience and structure of the team
	C7	Quality of Completed Projects	Previous projects quality
	C8	Company Age	The company's operational market presence
	C9	Experience in real estate	The company's or its shareholders' operational experience
Project Score (PS)	P1	Project-Environment Compatibility	Alignment with the surrounding area
	P2	Quality of Supervisory Staff	The expertise degree of supervisory team
	P3	Project Architecture	The functionality of the architectural design
	P4	Project attractively	The interest and attractiveness of the project units, equipment and location
	P5	Price level of proposed products	The adequacy between the proposed product and its price
	P6	Project Profitability	Investment minus costs
	P7	Units Required to Repay Loan	The % of units needed to cover the loan
	P8	Equity Financing Ratio	Equity on total investment
	P9	ESG	Environmental, Social and Governance impact
Market Score (MS)	M1	Macroeconomic context	Overall macroeconomic context including inflation, interest rates evolution, employment…
	M2	Property price index evolution	Local real estate market dynamic
	M3	Average monthly sales	The percentage of sales for ready to sell units
	M4	Stock on demand	The evaluation of the offer and demand
	M5	Accessibility Level	Ease of access to the project site
	M6	Safety Level	The project's security and safety
	M7	Noise level	Noise levels in the neighborhood
	M8	Pollution level	Pollution levels in the neighborhood
	M9	Proximity to amenities	Proximity to educational facilities, public transport options, dining and recreational services, healthcare services, major transportation routes, green spaces and recreational areas

Source: own study.

This overall score serves as a key decision-making tool, providing insights into a project's geographical advantages, financial stability, and alignment with prevailing market conditions. A good score reflecting a low risk project to finance should lead to loan approval, and a low score could give strong hints to deny the loan

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request. Each record is assigned a score based on the predicted probability of default generated by an XGBoost classifier, as shown in Formula (1).

$$RED\ RM\ Score = [1 - P(XGB)] \quad (1)$$

Where P(XGB) is the probability of default predicted by the XGBoost model (a value between 0 and 1). In this formulation, a higher score indicates a lower likelihood of default. The score is interpreted in a way that a higher value means the project is safer, making the score more intuitive for stakeholders who prefer a "creditworthiness" metric.

We have to mention that our study started out by setting a linear Formula (2), as can be seen below, based on traditional assessment reflecting experts' perception, but the results were not interesting even when combined with the previous formula:

$$Linear\ RED\ RM\ Score = [(40\% * \sum_{n=1}^{9} Cn * Wcn) + (30\% * \sum_{n=1}^{9} Pn * Wpn) + (30\% * \sum_{n=1}^{9} Mn * Wmn)] \quad (2)$$

where:

Cn - represents each of the 9 Company features listed in Table 2,

Wcn - represents each of the 9 assigned Company weights,

Pn - represents each of the 9 Project features,

Wpn - represents each of the 9 assigned Project weights,

Mn - represents each of the 9 Market features,

Wmn - represents each of the 9 assigned Marketweights.

Wcn, Wpn and Wmn are the importance scores converted to percentages based on XGBOOST classification and importance features.

In the linear formulation (Equation 2), the weights Wcn, Wpn, and Wmn were initially derived through a two-step approach:

1- an expert-driven Delphi method involving real estate risk analysts and credit officers (n = 10), who were asked to rank the relative importance of features in their credit decisions; and

2- statistical refinement, based on feature importance scores obtained from the XGBoost model.

The final weights were computed as a normalized average between expert rankings and model-derived importance metrics. This hybrid method was adopted to align domain knowledge with data-driven evidence, although it ultimately underperformed the XGBoost classification in predictive accuracy. The present study also tested some combined scoring with linear and machine learning prediction, but the retained formula outperformed these.

4. Case Study – Morocco's residential developers' dataset

4.1. Moroccan macroeconomic context

According to the 2024 General Population and Housing Census (RGPH) conducted by Morocco's High Commission for Planning (HCP), the country's legal population stands at 36,828,330, among which 20.9% are located in Casablanca (*Haut-Commissariat au Plan du Royaume du Maroc*, 2024). The population is growing and there is a big concentration in the economic capital.

In another perspective, the real estate sector has a significant impact on Morocco's economy, directly contributing by 6.3% to the Gross Domestic Product (GDP). This highlights the sector's importance in terms of investment and job creation.

According to Bank al Maghreb, 51.7 Billion MAD were distributed by September 2024 to finance real estate development. On the other hand, more than 246 Billion MAD financed real estate acquisitions proving then the dynamic of the sector (Bank Al Maghreb, 2024). For the construction sector, cement sales is a relying important indicator, showing the size and the dynamic of the market. Figure 3 below highlights the evolution for loan distribution as well as cement sales impacting and reflecting the sector dynamics from 2023 to 2024. We notice increasing values from one quarter to another highlighting consequently the positive evolution of projects developed and under construction in this period.

To complete a quick overview, here are some of macroeconomic indicators for Morocco:

- A GDP growth rate of 3.4% in 2023 thanks to tourism, manufacturing exports, and high private consumption. (World Bank Group, 2024).
- In 2023, Bank Al Maghrib increased the key interest rate three times to elevate it from 1.5% to 3% in order to control inflation. Then in June 2024, Morocco's central bank reduced it to 2.75% to stimulate economic activity. (Bank Al-Maghrib, 2024).
- Inflation has been declining in 2024. In October, the annual inflation rate eased to 0.7% from 0.8% in September, primarily due to stable food prices (Morocco's Annual Inflation Drops to 0.7% in October, 2024).
- The unemployment rate in Morocco averaged

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10.2% over the decade. Recent data indicates a slight improvement, with the rate decreasing to 9.9% in 2023, reflecting gradual economic recovery efforts.
- Various tax reforms and government incentives were implemented to attract foreign investment and stimulate economic growth.
- With its constitutional monarchy and a history of gradual political reforms, the country is considered one of the more politically stable countries in the region.

Although ESG was included via proxies, such as developer lawsuit history, zoning alignment, future work could include clear ESG scoring integration.

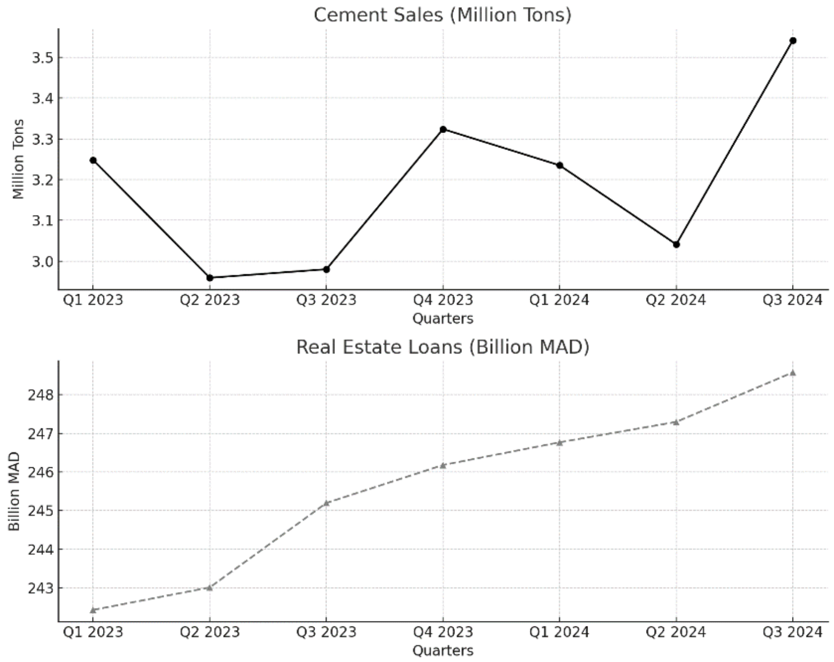

Fig. 3. Key indicators for Construction Sector (Flash Indicateurs - Observatoire de l'habitat, 2024). *Source*: own study.

4.2. Moroccan Real Estate market – Zoom into Casablanca, the Moroccan economic capital

According to the Ministry of National Territorial Planning, Town Planning, Housing and Urban Policy, in 2023, more than 262 K-Housing units were produced (+5.24% compared to 2022) and more than 320 K were under construction (+59.42% compared to 2022) (Ministère de l'Aménagement du territoire national, de l'Urbanisme, de l'Habitat et de la Politique de la ville, 2024). Furthermore, the semestrial report of the ministery (Actualités immobilières, 2024) highlights that the Moroccan real estate market is showing significant signs of revitalization in 2024, driven by government initiatives and a substantial return of Moroccans residing abroad (MRE).

For the market evaluation, an indicator labeled IPAI (stands for Indice des Prix des Actifs Immobiliers, translated as the Real Estate Asset Price Index) is used in Morocco to track the evolution of real estate prices. It provides an aggregate measure of price changes for different types of real estate assets, such as residential properties, commercial properties, and urban land. The IPAI is jointly published by Bank Al-Maghrib (Morocco's central bank) and ANCFCC (National Agency for Land Registration, Cadastre, and Cartography responsible for managing property registration, maintaining cadastral data, and producing maps in Morocco). It is calculated using a hedonic price model, which adjusts for the quality and characteristics of real estate assets to ensure accurate price comparisons over time. The IPAI is widely used in Morocco to guide real estate investments, policy-making, and credit risk analysis. In Figure 4 below, we present the trends of IPAI and transactions from Q1 2023 to Q4 2024 for different properties types in Casablanca. Even though there was reduction of transactions in 2024 Q1, it was due to other fiscal factors announced in this period impacting the delay in some transactions. The IPAI variation is generally in evolution, with mean stable variation encouraging transactions.

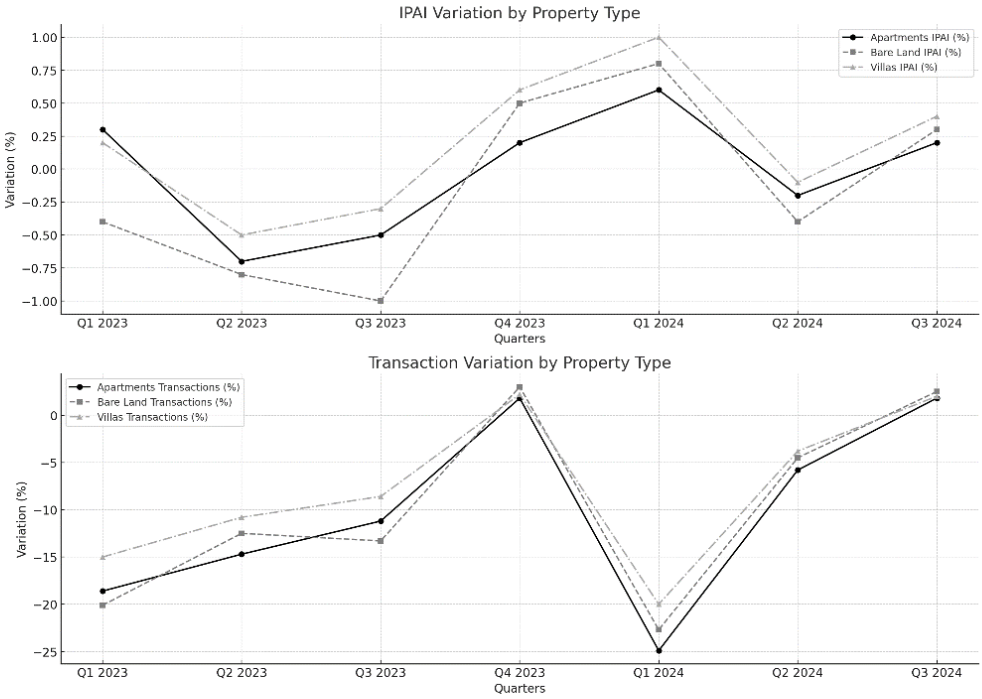

Fig. 4. IPAI and transactions variation for apartments in Casablanca (ANCFCC, 2024). *Source*: own study.

4.3. RED RM implementation

In order to test the model, we undertook the process to score with the grid. We first start by the Data manipulation process.

4.3.1. Data Collection, selection and preparation

For data collection, it was thus necessary to put in place a process to collect and merge with existing data, in order to further test with financed projects to evaluate the efficiency of the model not only with experts perspective but also with a real set of projects.

For data collection, each item of the dataset was collected and evaluated. We completed with previous identified features for 653 different financed projects in Morocco. The dataset includes data sourced from credit portfolios of Moroccan banks (2016–2021), enriched with open GIS data, regulatory disclosures, and institutional records. Criteria included financial completeness, identifiable location, and finalized loan issuance.

First, we collect key attributes such as financial metrics (e.g., profitability, equity ratio, etc.) and other data. For incomplete or inexistent features, we complete it with web scraping and manual collection.

Concerning data selection, we perform a machine learning alogorithm (XGBoost) to select the most important features and combine them with the most important ones from experts' perspective. For the present case study, the selected features are those listed in the RED RM grid. For other larger case studies with different datasets, the features could be readjusted.

For data preparation, we calculate financial ratios based on financial statements of the company.

4.3.2. Data encoding

Each variable is encoded into a 3-level scale. For each feature, the different values are encoded to appreciate if it is a poor, an average or high value according to its performance and impact to evaluate the features on the same base. If the value is Poor, it is scored "1", if it is average, it is encoded "2" and if it is high, it is encoded "3".

Figures 6 through 9 show the XGBoost model's determined risk level distribution and classification. Predicted probability thresholds underlie the color-coded risk classifications, i.e.: Low (green), Medium (yellow), and High (red): low risk below 0.3, medium risk between 0.3 and 0.6, and high risk above 0.6. Establishing these thresholds was facilitated by quantile-based segmentation of the development dataset. The variables included are market saturation, developer history, project financial strength, and site qualities. High-risk projects' spatial concentration in some metropolitan peripheries emphasizes how location and regulatory friction affect project viability.

The RED RM model estimates the probability of default over a three-year horizon, which aligns with the typical project lifecycle in real estate development, from financing and permitting through construction and initial sales. This timeframe was selected based on empirical observation of project durations in the dataset and expert feedback.

Consistent and interpretable XGBoost model default probability thresholds define the risk classes Low, Medium, and High, therefore providing consistency and interpretability. Expert advice let one evaluate these derived from empirical quantile segmentation criteria. A score less than 0.3 is especially low risk, meaning programs with strong bases and appropriate market conditions. Between 0.3 and 0.6 implies medium risk which refers to minimal context-dependent risk factors. Usually pointing to sensitive market areas, inadequate financial structure, or inexperienced developers, high risk ratings are above 0.6. This classification gives statistical validity coupled with interpretability for lenders' and investors' decision-making process.

4.4. Dataset description and visualization

The dataset comprises 653 real estate development projects financed between 2016 and 2025 in Morocco. The following Figure 5 presents the distribution of these projects with the default perspective. The chart shows the overall class imbalance, with 538 non-defaulting (class 0) and 115 defaulting (class 1) projects. The second chart presents the yearly distribution of defaults. While the number of financed projects shows a decreasing trend post-2018, default rates exhibit volatility, with spikes in 2019 and again in 2024, reflecting macroeconomic shocks or project pipeline changes. This temporal distribution suggests the necessity for time-aware risk modeling with a mid-term predictive horizon.

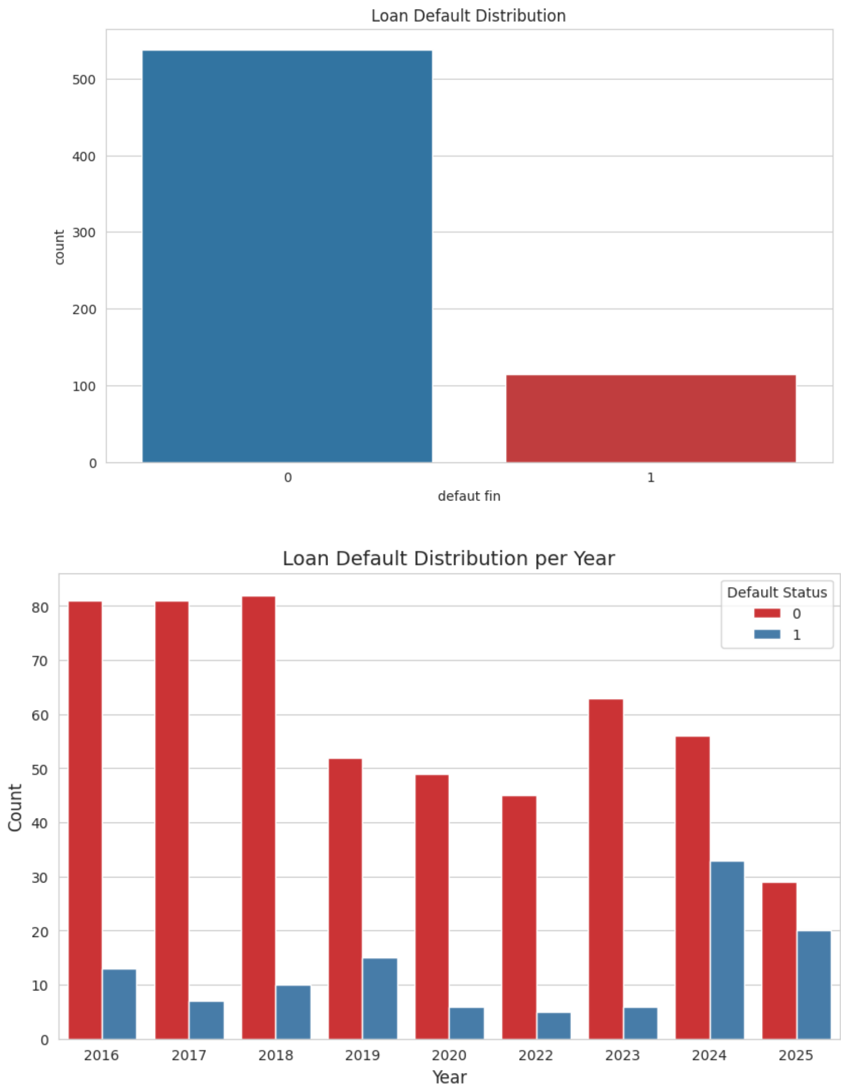

Fig. 5. Distribution of dataset (Default perspective and default per year). *Source*: own study.

For data sources, we want to highlight that credit committee studies and bank loan portfolios (anonymized records to respect data privacy) provided financial data. National urban planning organizations, public real estate registries, and open-source GIS layers provided spatial and market data. Regulating filings and internal due diligence records helped to gather institutional and developer-related information. This multifarious dataset offers a strong and context-rich risk modeling system.

4.5. Results - RED RM

After encoding the dataset and using XGBoost to predict defaults, we obtained the results shown in Figures 7 and 8. For risk classification, we defined three classes using probability thresholds of 30% and 70%.

Figure 6 presents the ROC curves for the three tested models (XGBoost, Random Forest, and Logistic Regression) used to predict project default. All models exhibit an excellent discriminatory power, with AUC values exceeding 0.998, indicating almost perfect classification. The near-overlapping curves suggest comparable performance, although XGBoost was retained for its computational efficiency and better feature interaction handling.

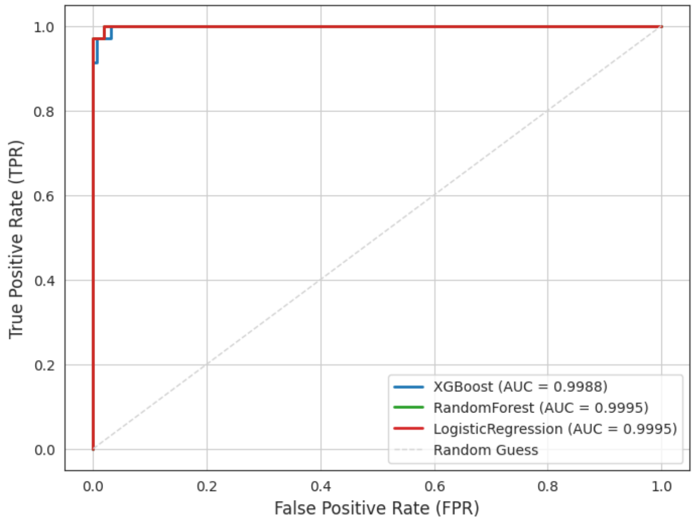

Fig. 6. ROC Curve comparison. *Source*: own study.

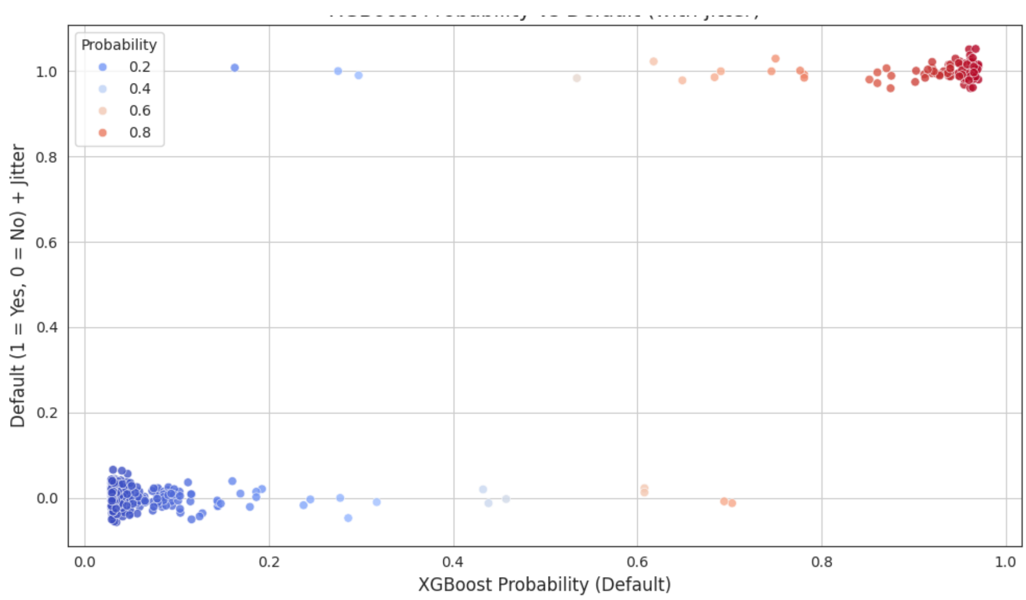

Fig. 7. XGBoost Probability of default vs real default. *Source*: own study.

Figure 7 presents the relationship between the predicted probability of default by XGBoost and the actual default outcomes. Projects are gray scale coded by risk category (Low, Medium, High) based on defined probability thresholds (<0.3, 0.3–0.6, >0.6). The scatterplot includes vertical jitter for the binary default outcome (1 = Default, 0 = No Default). The clear separation between low-probability non-defaulters and high-probability defaulters demonstrates the model's strong predictive capacity and well-calibrated thresholding strategy.

To enhance precision in our visualizations, we employed a scatter plot with a slight jitter on the y-axis to avoid overplotting of the binary default variable.

In the following Table 3, the metrics are listed to confirm the good performance of the tested algorithms showing good results for the all of them. Even if the other algorithms show better performances, we choose XGBoost for our model. We have used 10 cross validation and SMOTE to improve the model performance.

Table 3

Algorithms / Metrics comparison

Algorithm / Metric	Accuracy	Precision	Recall	F1-score
XGBoost	0.9847	0.9444	0.9714	0.9577
Random Forest	0.9949	1.0000	0.9714	0.9855
Logistic Regression	0.9847	0.9211	1.0000	0.9589

Source: own study.

Although Random Forest and Logistic Regression demonstrated slightly higher performance on certain metrics, we ultimately chose XGBoost for our model because of its overall robustness and superior ability to capture complex, non-linear relationships.

Furthermore, we compared these machine learning results with a traditional linear scoring method, in which all features were combined using weights derived from their respective importances. Our analysis revealed that the linear approach was less effective at correlating with actual default outcomes.

In the following Figure 8, we display the comparison between the linear RED_RM scoring approach and actual default outcomes. The scatterplot, with added vertical jitter, highlights the limited discriminative power of the linear score. While some separation exists, especially at the extremes (scores near 0 or 1), a large cluster of medium-risk projects (centered around 0.4–0.6) overlaps with both defaulting and non-defaulting cases. This confirms the superior classification capacity of non-linear models like XGBoost, which better capture interactions and non-obvious risk patterns across features.

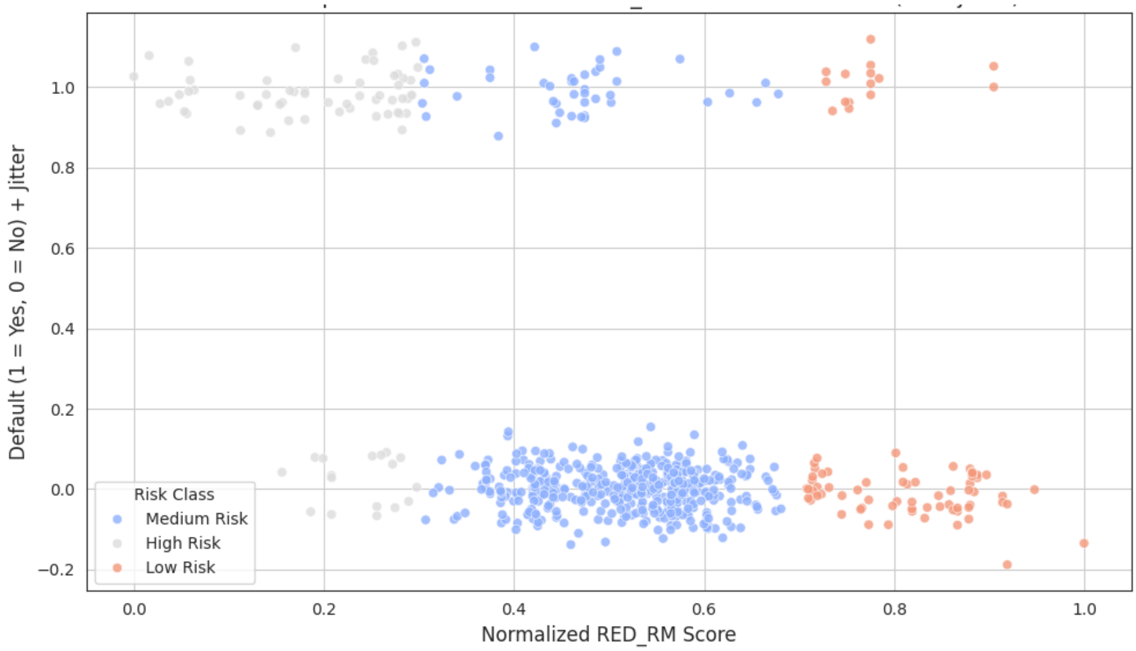

Fig. 8. Relationship between normalized scoring and default. *Source*: own study.

We minimized overfitting and guaranteed model dependability by using a 10-fold cross-valuation technique. Across folds the dataset was randomly divided into 80% training and 20% test sets. Every fold guaranteed balanced class representation for the minority class via SMOTE.

The results of the study are good as it captures beyond linear relationships and allows to score better, with high probability of success using machine learning supervised algorithm XGBoost. Similar studies employing financial datasets with engineered features (Dai et al., 2021; Qin et al., 2021) match the high accuracy recorded (over 98%). Model robustness benefited from thorough feature selection and SMote application. Still, more outside validation would guarantee generalizability.

The model gives a practical rating grid and hints to customize it depending on the context to contribute in the improvement of the decision making process concerning real estate development financing for banks or other financial institutions. This can also be tested by investors to decide to invest in a specific project. Consequently the decision will be to avoid and decline the request or to require more warranties or

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raise the interest rate or to lower the amount to lend for higher Loan to Value (LTV). Moreover, smart cities adoption and deployment (Moumen et al., 2024) will strengthen the market scoring for better results.

We have to mention that first we investigated several models including artificial neural networks (ANN), K-Nearest Neighbors (KNN), and Support Vector Regression (SVR). These, however, either produced reduced accuracy or required more rigorous tuning and processing resources without appreciable performance improvement. Although it is considered as strong, ANN lacks the openness necessary for decision-making in controlled financial systems.

4.6. Sensitivity analysis and application scenarios

We performed a feature relevance study employing SHAP (SHapley Additive exPlanations) values to evaluate the stability of the model and the contribution of every variable to the final risk score. This approach estimates, over all observations, the marginal contribution of every input characteristic to the forecasts of the model. The equity financing ratio, prior project success rate of the developer, average monthly sales, and accessibility to important metropolitan facilities turned out to be the most influential elements. We then performed a sensitivity test by perturbing particular elements (±10%) over a random subsample to augment this. With less than 3% of projects moving from one risk category to another, the findings revealed that the model's classification remained strong, hence verifying its resistance to modest input variability.

Moreover, we create two example-based scenarios from the dataset to show useful applications of the RED RM model. In the first, a high-risk project driven by an inexperienced developer in a peri-urban location with minimal regulatory transparency and limited equity funding gets a risk score above 0.8. Usually, such a profile calls for collateral review or causes loan denial. On the other hand, a low-risk project in a desirable metropolitan area with an experienced sponsor, stable financial structure, and positive market dynamics gets a risk score below 0.2, thus justifying fast-track approval and good financing terms. These illustrations show how well the model fits to project-specific profiles, therefore guiding credit selections.

The present version of the RED RM model was only created and tested using data from Moroccan real estate projects. However, we know that external validation is important for making sure that the model can be used in other situations as well. At this point, there has been no empirical or synthetic validation utilizing data from other geographic or regulatory settings. The model's structure was made to be modular, which means it can be changed to fit different situations as long as the right financial, spatial, and market data are available. We realize that things like differences in institutional frameworks, risk perception, and data granularity could make the model less useful in other places. Future studies will focus on testing the RED RM model in various developing and developed markets to see how well it performs in risk situations, real estate practices, and regulatory systems unique for those areas.

5. Discussion

This paper offers a useful, location-based rating model including important elements affecting the real estate market, real estate developers, project feasibility, and loan repayment capacity. Aiming to enhance decision-making, the proposed model consists of a data process and a grid with algorithms to evaluate every real estate finance demand for banks and investors. By means of their recognized characteristics, assigning a score to each company, the project, and the market helps to evaluate each financing need, so considering the particularities of every component.

Feature impact was assessed using SHAP values to help reduce the interpretability issues of XGBoost, which is still complicated, even with its predictive strength. Ten-fold cross-valuation with L2 regularization also validated the model. Under controlled input perturbations, sensitivity analysis indicated above 97% classification consistency, hence strengthening the resilience of the model. Still, its efficiency relies mostly on the quality and representativeness of the dataset, which might not adequately reflect the actual complexity. Moreover, despite addressing class imbalance through SMOTE, potential risks of overfitting and data leakage persist.

Governance proxies such as historical litigation and regulatory compliance help to indirectly capture current ESG-related elements. Future work will incorporate explicit sustainability indicators, like environmental performance or social impact indices, as soon as such data become available. This will enable closer alignment with global banking sustainability standards. It will also use a more advanced market valuation as presented in our work (Imane et al., 2025).The model's applicability across diverse regulatory, economic, or spatial contexts still requires validation. In highly volatile economies, augmenting the model with temporal components or macroprudential overlays could increase resilience.

The RED RM model can be used, not only by banks and investors, but also by other real estate stakeholders. It might also be useful for the public sector. Governments could use RED RM as a strategic planning tool to find urban areas that aren't doing well, predict if a project will work, or decide which infrastructure expenditures to make first in places with a lot of promise. Also, combining RED RM with public housing policy frameworks could help make data-driven choices about zoning, putting affordable housing in the right places, and making the best use of property. Future versions of the model may have modules that are specifically designed for urban planning agencies and setting priorities for public expenditure.

6. Conclusion

This model proposes a flexible framework for professionals in changing legal environments and real estate conditions. Its interaction with financial systems could help to improve consistency and openness, hence strengthening loan approval processes improving the decision making process.

Apart from its ability to anticipate, the RED RM model provides banks and investors with practical means to include official, data-driven criteria into project assessment. Its modular design supports dataset-based adaptability worldwide.

We must nonetheless admit that the model has its limitations as well. Its success depends on the quality and completeness of the input dataz so, even with best attempts to guarantee resilience by sensitivity analysis and cross-validation, real-world variability could lower precision.

Richer ESG measurements, the application of longitudinal data for dynamic risk modeling, and the translation of RED RM to other areas with different market dynamics and with temporal variation should all be investigated in future work. Additionally helping to improve usability and operational integration into decision-support systems are pilot projects involving financial institutions. Eventually, more development will focus on embedding RED RM into real-time systems to enable transparent real estate lending policies and agile architecture.

Statement

The datasets and code used to develop the RED RM model are not publicly available due to confidentiality agreements. However, anonymized samples and the model's implementation scripts can be made available by the authors upon reasonable request.

References

Ababsa, M. (2024). Real estate in the Middle East: An economy shaped by rents. *Globalization and Dynamics of Urban Production*, 177-212.

Actualités immobilières. (2024, juin). *Ministère de l'Aménagement du Territoire National, de l'Urbanisme, de l'Habitat et de la Politique de la Ville*. https://www.mhpv.gov.ma/fr/veille_habitat/

Anand, M., Velu, A., & Whig, P. (2022). Prediction of loan behaviour with machine learning models for secure banking. [JCSE]. *Journal of Computing Science and Engineering: JCSE, 3*(1), 1–13. Advance online publication. https://doi.org/10.36596/jcse.v3i1.237

ANCFCC. (2024, juin). *IPAI et transactions*. https://www.ancfcc.gov.ma/IndicePrixImmobiliers/

Anelli, D., & Tajani, F. (2023). Spatial decision support systems for effective ex-ante risk evaluation: An innovative model for improving the real estate redevelopment processes. *Land Use Policy*, *128*, 106595. https://doi.org/10.1016/j.landusepol.2023.106595

Bank Al Maghreb. (2024, octobre). *Tableau de bord - Crédits dépôts bancaires*" [Dashboard - Loans and deposits]. Bank Al-Maghrib. https://www.bkam.ma/fr/Statistiques/Chiffres-cles-de-l-economie-nationale/Credits-et-depots-bancaires

Bank Al-Maghrib. (2024). *Bank Al-Maghrib*. https://www.bkam.ma/

Barbaglia, L., Manzan, S., & Tosetti, E. (2023). Forecasting loan default in Europe with machine learning. *Journal of Financial Econometrics*, *21*(2), 569–596. https://doi.org/10.1093/jjfinec/nbab010

Barmeier, M., Liebeg, D., & Rötzer, S. (2024). Systemic risks from commercial real estate lending of Austrian banks. *Financial Stability Report, 48*, 31–39.

Berrada, I. R., Barramou, F. Z., & Alami, O. B. (2022). A review of Artificial Intelligence approach for credit risk assessment. *2022 2nd International Conference on Artificial Intelligence and Signal Processing (AISP)*, 1-5. https://doi.org/10.1109/AISP53593.2022.9760655

Chen, Z.-S., Zhou, J., Zhu, C.-Y., Wang, Z.-J., Xiong, S.-H., Rodríguez, R. M., Martínez, L., & Skibniewski, M. J. (2023). Prioritizing real estate enterprises based on credit risk assessment: An integrated multi-criteria group decision support framework. *Financial Innovation, 9*(1), 120. https://doi.org/10.1186/s40854-023-00517-y

Cupal, M. (2014). The comparative approach theory for real estate valuation. *Procedia: Social and Behavioral Sciences, 109*, 19–23. https://doi.org/10.1016/j.sbspro.2013.12.414

Dai, Z., Yuchen, Z., Li, A., & Qian, G. (2021). The application of machine learning in bank credit rating prediction and risk assessment. *2021 IEEE 2nd International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE)*, 986-989.

Droj, G., Kwartnik-Pruc, A., & Droj, L. (2024). A comprehensive overview regarding the impact of GIS on property valuation. *ISPRS International Journal of Geo-Information, 13*(6), 175. https://doi.org/10.3390/ijgi13060175

Finalising Basel III - In brief. (2017).

Flash Indicateurs—Observatoire de l'habitat [Flash indicators - Housing Observatory]. (2024). *Ministère de l'Aménagement du Territoire National, de l'Urbanisme, de l'Habitat et de la Politique de la Ville*. https://www.mhpv.gov.ma/fr/flash-indicateurs/

Haut-Commissariat au Plan du Royaume du Maroc [High Commission for Planning of the Kingdom of Morocco]. (2024). Site institutionnel du Haut-Commissariat au Plan du Royaume du Maroc. https://www.hcp.ma

Hellström Ängerud, L. (2017). *Credit risk assessment of real estate companies: How does the credit assessment of banks and bond* *investors differ?* https://www.diva-portal.org/smash/record.jsf?pid=diva2:1127817

Horvátová, E. (2024). The residential real estate market in the Slovak Republic. In: M. Augustín, P. Jančovič, & B.S. Sergi (Eds.), *Modeling economic growth in contemporary Slovakia* (pp. 101–120). Emerald Publishing Limited. https://doi.org/10.1108/978-1-83549-454-720241008 https://www.emerald.com/insight/content/doi/10.1108/978-1-83549-454-720241008/full/html

Imane, R. B., Fatimazahra, B., & Omar, B. A. (2025). Real estate market scoring. *2025 5th International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET)*, 1-7. https://ieeexplore.ieee.org/abstract/document/11008118/

Jouahri. M. A., & de Bank Al-Maghrib, G. (2009). "*Le Maroc Face a La Crise Et a L'apres-Crise*" *[Morocco facing the crisis and after crisis]*. https://www.bkam.ma/fr/content/download/360884/3034455/InterventionLINKS.pdf

Khandaskar, S., Panjwani, C., Patil, V., Fernandes, D., & Bajaj, P. (2023). House and rent price prediction system using regression. *2023 International Conference on Sustainable Computing and Smart Systems (ICSCSS)*, 1733-1739. https://ieeexplore.ieee.org/abstract/document/10169290/

Lausberg, C., & Krieger, P. (2021). Rules for a coherent real estate risk scoring. *Journal of European Real Estate Research, 14*(1), 1–18. https://doi.org/10.1108/JERER-01-2020-0001

Locurcio, M., Tajani, F., Morano, P., & Anelli, D. (2021). A multi-criteria decision analysis for the assessment of the real estate credit risks. In P. Morano, A. Oppio, P. Rosato, L. Sdino, & F. Tajani (Eds.), *Appraisal and Valuation* (pp. 327–337). Springer International Publishing. https://doi.org/10.1007/978-3-030-49579-4_22

Mete, M. O., Guler, D., & Yomralioglu, T. (2022). Towards a 3D real estate valuation model using BIM and GIS. In M. Ben Ahmed, A. A. Boudhir, İ. R. Karaș, V. Jain, & S. Mellouli (Eds.), *Innovations in Smart Cities Applications* (vol. 5, pp. 945–962). Springer International Publishing. https://doi.org/10.1007/978-3-030-94191-8_77

Ministère de l'Aménagement du territoire national, de l'Urbanisme, de l'Habitat et de la Politique de la ville [Ministry of National Territory Planning, Urban Planning, Housing, and City Policy]. (2024, septembre). *Observatoire de l'habitat*. Ministère de l'Aménagement du Territoire National, de l'Urbanisme, de l'Habitat et de la Politique de la Ville. https://www.mhpv.gov.ma/fr/

Mooya, M. M. (2016). *Real estate valuation theory*. Springer Berlin Heidelberg., https://doi.org/10.1007/978-3-662-49164-5

Morocco's annual inflation drops to 0.7% in October. (2024, novembre 22). *Reuters*. https://www.reuters.com/world/africa/moroccos-annual-inflation-drops-07-october-2024-11-22/

Moumen, N., Radoine, H., Nahiduzzaman, K. M., & Jarar Oulidi, H. (2024). Contextualizing the smart city in Africa: Balancing human-centered and techno-centric perspectives for smart urban performance. *Smart Cities, 7*(2), 712–734. https://doi.org/10.3390/smartcities7020029

Naeem, N., Rana, I. A., & Nasir, A. R. (2023). Digital real estate: A review of the technologies and tools transforming the industry and society. *Smart Construction and Sustainable Cities, 1*(1), 15. https://doi.org/10.1007/s44268-023-00016-0

Nejjar, C., Kaicer, M., Haimer, S. E., Idhmad, A., & Essairh, L. (2024). Credit risk management in microfinance: Application of non-repayment prediction models. In M. Ezziyyani, J. Kacprzyk, & V. E. Balas (Éds.), *International Conference on Advanced Intelligent Systems for Sustainable Development (AI2SD'2023)* (Vol. 930, p. 301-308). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-54318-0_26

Qin, C., Zhang, Y., Bao, F., Zhang, C., Liu, P., & Liu, P. (2021). XGBoost optimized by adaptive particle swarm optimization for credit scoring. *Mathematical Problems in Engineering, 2021*, 1–18. https://doi.org/10.1155/2021/6655510

Renigier-Biłozor, M., & Chmielewska, A. (2019). A rating system for the real estate market. *Argumenta Oeconomica, 2*, 427–458. https://doi.org/10.15611/aoe.2019.2.18

Rhzioual Berrada. I., Barramou, F., & Bachir Alami, O. (2024). Towards a machine learning-based model for corporate loan default prediction. *International Journal of Advanced Computer Science & Applications, 15*(3). https://search.ebscohost.com/login.aspx?direct=true&profile=ehost&scope=site&authtype=crawler&jrnl=2158107X&AN=176379054&h=R%2BbOWNG8CHAB80a6OT0xnCNoeVJq5xsSUV09PwIDbbXARVioeDiWW3roDhqiNFry6%2FZOHLFM0Z48hxSb7%2BqCig%3D%3D&crl=c

Siddiqi, N. (2017). *Intelligent credit scoring: Building and implementing better credit risk scorecards*. John Wiley & Sons. https://books.google.com/books?hl=fr&lr=&id=q-qoDQAAQBAJ&oi=fnd&pg=PR13&dq=Intelligent+credit+scoring:+Building+and+implementing+better+credit+risk+scorecards&ots=JkCpyCARUr&sig=-8phdVYr3JWJNFNbvDeEwte__FI https://doi.org/10.1002/9781119282396

Surgelas, V., Puķīte, V., & Arhipova, I. (2024). Property valuation in latvia and Brazil: A multifaceted approach integrating algorithm, geographic information system, fuzzy logic, and civil engineering insights. *Real Estate, 1*(3), 229–251. https://doi.org/10.3390/realestate1030012

World Bank Group. (2024, juillet 17). *Morocco Economic Monitor – Summer 2024 Morocco's Economy Proves Resilient but Private Sector Faces Challenges*. World Bank. https://www.worldbank.org/en/country/morocco/publication/morocco-economic-monitor-summer-2024-morocco-s-economy-proves-resilient-but-private-sector-faces-challenges

Xu, Y., Li, J., & Wu, A. (2024). An XGboost algorithm based model for financial risk prediction. *Tehnički Vjesnik (Strojarski Fakultet), 31*(6), 1898–1907.

Zanin, L. (2022). Estimating the effects of ESG scores on corporate credit ratings using multivariate ordinal logit regression. *Empirical Economics, 62*(6), 3087–3118. https://doi.org/10.1007/s00181-021-02121-4

Zhang, L., Wang, J., & Liu, Z. (2023). What should lenders be more concerned about? Developing a profit-driven loan default prediction model. *Expert Systems with Applications, 213*, 118938. https://doi.org/10.1016/j.eswa.2022.118938