MJQQR

ISSN 2665-8623

Artificial Intelligence and Machine Learning in Green Credit Scoring: Opportunities and Behavioral Challenges

Kabira ZOUMAK[1*], *Khadija* ANGADE[2]

[1]Laboratory of Research in Management of Performance for Public, Private Organizations and Social Economy MAPES, Ecole Nationale de Gestion et de Commerce d'Agadir, Ibn Zohr University, Agadir, Morocco

[2]Laboratory of Research in Management of Performance for Public, Private Organizations and Social Economy MAPES, Ecole Nationale de Gestion et de Commerce d'Agadir, Ibn Zohr University, Agadir, Morocco

Abstract. Within the current global framework, green credit serves as a key lever for financing the sustainable transition of the economy. Thus, the nation of Morocco has considered green investment as the main cornerstone of its economic strategy. Yet, the dual requirements of financial performance and environmental impact make its assessment more complicated. Indeed, the introduction of artificial intelligence (AI) and machine learning (ML) into credit scoring offers new opportunities in terms of efficiency, accuracy, and detection of sustainability-related risk, according to the current literature. However, when it comes to the notion of "green", these innovations are met with behavioral resistance and different perceptions within financial institutions, namely banks, where trust in algorithmic models and risk culture plays a crucial decisive role. The main aim of this research is to analyze to what extent behavioral variables impact the acceptance of AI- and ML- based scoring models specifically applied to green credit. To address this problem, the study adopts a mixed-method approach combining a quantitative survey and semi-structured interview with a total of 120 stakeholders. The results revealed that green credit scoring, unlike traditional credit scoring, relies on decision-making processes that integrate ethical values and increased sensitivity to environmental reputation risk.

Keywords. green credit, artificial intelligence, machine learning, behavioral variables, Morocco.

*Corresponding author:kabira.zoumak@edu.uiz.ac.ma

1 Introduction

Moving towards a sustainable economy is now essential for every economic actor within the global context of the climate emergency and the digital transformation of the financial sector. Green finance has evolved into a central mechanism for influencing the flow of capital to low-carbon activities by integrating environmental, social and governance (ESG) metrics into funding and investment decisions. Among the green finance tools, green credit is one of the most important, as it ought to be directed to businesses and projects with direct environmental benefits. The main objective is to facilitate economic growth while promoting environmental sustainability by linking financial performance to environmental outcomes [1)].

In fact, green finance is one of the pillars of Morocco's economic transition, as it was set out in the National Sustainable Development Strategy [2]. In line with the Kingdom's commitments at both national and international levels, commercial banks have to contribute to green project financing. Despite these institutional advances, a set of challenges remains that is facing the Moroccan banking industry in assessing credit risk related to green initiatives [3]. Actually, in the case of projects with a high level of innovation, for which environmental externalities are difficult to evaluate, such traditional scoring models may not be adapted, being mainly based on past financial data. These limits could consequently result in loan rationing and possibly deter sustainable companies, slowing down the ecological revolution.

However, the latest breakthroughs in artificial intelligence (AI) and machine learning (ML) have overcome many of the limitations involved [4-6]. If huge and varied data sets with behavioral features, climatic exposure, and ESG measurements are available [7], it would appear that AI- and ML-based scoring models may enhance accuracy, speed, and objectivity in risk assessment [4, 8, 9, 10]. Moreover, they are able to help pinpoint non-linear patterns, reducing human bias and enhancing inclusiveness in sustainable finance. As Fuster et al. suggest, when combined with AI and ML, green credit scoring will have a more level playing field in distribution, adding value toward achieving sustainable development goals [11].

There are serious organizational, ethical, and behavioral issues with this technological shift. Although the design of the risk culture, clarity of the model, and trust in algorithms remain valid factors, banking organizations also face resistance to the use of algorithmic tools in financial decision-making. Researchers have pointed out the problem of algorithm aversion, in which human decision-makers like to mock and distrust suggestions coming out of computer models, even when the accuracy of the models has been thoroughly checked. The application of AI/ML in green finance would thus require not just technical performance of the adopted algorithms but also behavioral factors affecting perceived utility, organizational trust in the technology, transparency of decision-making, and the technology's compatibility with institutional culture and procedures [7,12].

This tension between technological innovation and human acceptance makes the study of behaviorism in green finance very relevant. Whereas the literature increasingly acknowledges the potential of AI and ML to improve sustainable finance [13], little research has been conducted on its behavioral determinants in the context of emerging economies. In Morocco, where digitization is increasing in the banking sector but still constrained by structures and traditional risk cultures, the success of these tools is fraught with problems requiring an understanding of what drives trust and disposition to act towards them.

In this context, this research analyses the influence of behavioral variables, such as perceived usefulness, perceived transparency, organizational trust, and adoption intention, on the acceptance of AI- and ML-based scoring models applied to green credit. Guided by three complementary theoretical perspectives — *technological theory*, *behavioral finance theory*, and *sustainable/institutional theory* —, an integrated approach has been taken in this study, linking technological innovation, human behavior, and environmental responsibility.

The research will cover the following questions:

- How are the accuracy and inclusivity of green credit scoring enhanced by artificial intelligence and machine learning techniques?
- What are the behavioral aspects that influence financial decision-makers' adoption and trust of automated scoring models?
- What are the primary motivators for Moroccan banks' and institutions' use of AI- and ML- based green grading systems?

As stated in the above abstract, a mixed-methods approach will be used to guide the current study, combining quantitative survey analysis with qualitative interviewing with a total of 120 stakeholders in the Moroccan banking industry including credit managers, risk analysts, sustainable finance specialists, and data scientists. Through its contribution theoretically and managerially, this study helps in understanding the conditions for ethical and successful implementation of AI and ML-based models in the Moroccan banking sector, focusing on connections between innovation, human behavior, and environmental responsibility. As a result, this research paper opens the way for a more transparent, equitable, and sustainable finance, where technology is actually a catalyst for environmental transformation.

The remainder of this paper is organized as follows. Section 2 presents the definitions of the key concepts and develops the conceptual model underpinning the study, drawing on the literature on artificial intelligence and machine learning, green finance, and green credit, as well as relevant theoretical perspectives. Section 3 describes the research methodology, adopting a hypothetico-deductive mixed-methods approach that combines qualitative interviews with quantitative validation to examine the behavioral and organizational determinants of AI/ML adoption in green credit scoring. Section 4 reports the empirical results of both qualitative and quantitative analyses. Section 5 discusses these findings in light of the proposed conceptual framework and existing literature. Finally, Section 6 concludes the paper by summarizing the main findings, outlining theoretical and managerial implications, and highlighting the study's limitations and directions for future research.

2 Literature Review

2.1 Definition and Emergence of AI and ML

Artificial Intelligence (AI) refers to a combination of techniques and systems that can carry out operations like vision, language comprehension, logical inference, planning, and decision-making that often call for human intellect. John McCarthy and his associates formalized artificial intelligence in the 1950s, laying the foundation for a field of study that sought to replicate certain aspects of human cognition. From an initial focus on rigid symbolic and logical systems, AI moved over the years to machine learning (ML) and big data analytics techniques that have allowed machines to solve complex problems and adapt to changing environments [14].

A very significant part of artificial intelligence is machine learning, which refers to a set of methods allowing the system to learn from data, draw conclusions from it, and improve its performance without explicit programming [15]. Machine learning models determine their parameters based on the observed data for optimal prediction or classification, opposed to classical algorithms that solve the problem by iterating through a series of predetermined steps. The major approaches [16]:

- Supervised learning: The input characteristics are linked with matching output labels in the labeled data used to train the model. Learning a mapping from inputs to outputs is the aim in order to forecast fresh data.

- Unsupervised learning: In order to find hidden patterns in the data, the model is trained using unlabeled data. Dimensionality reduction and clustering are typical tasks.
- Reinforcement learning: The model seeks to maximize cumulative rewards over time by interacting with its surroundings and getting rewards or penalties for its activities.
- Semi-supervised learning: That integrates labeled and unlabeled data aiming to improve learning accuracy, often used when labeled data is scarce or expensive to obtain.

Since then, some of these methods have been applied to a wide range of financial applications, including portfolio optimization, fraud detection, and payment default prediction. In recent years, machine learning has been introduced to green credit rating to encompass various financial and nonfinancial conditions, such as market behavior, climate data, and ESG indicators that further enhance the rating process in terms of appropriateness, efficiency, and objectivity. The development of AI and ML also coincides with the technological environment that is never more diverse and granularly available for sustainable finance analysis because of the big bang of sources, such as social media, ESG reports, satellite data, climate databases, which further enable responsible, adaptive, and predictive finance [17-19].

2.2 Definition and Emergence of Green Finance, Green Credit and Credit scoring

The term "green finance" refers to a range of instruments, processes, and practices utilized in decision-making and incorporates elements that are connected to social, environmental, and governance standards in capital allocation. In the context of the Paris Agreement and the Sustainable Development Goals (SDGs), the ultimate purpose of green finance is to raise and allocate funds for sustainable initiatives as a means of reducing carbon footprints and helping to achieve key climate-related objectives at a global level [1].

Green credit as a strategic tool can be defined as lending provided for projects whose environmental impact can be identified and quantified [20]. It includes the following: a circular economy, clean resource management, efficient usage of energy, pollution emission reduction, and renewable energy. Unlike a normal loan, the actual green credit evaluation has two parts: the real environmental contribution of the project and the financial capacity of repayment. The contribution can be quantified by Environmental Performance Indicators (EPIs) and adherence to ESG guidelines, but it complicates the evaluation process [13,21]. In this context, through the National Sustainable Development Strategy 2030 [2], Morocco has identified a role for commercial banks in financing sustainable projects, with green financing as a lever for low carbon economy, ecological transition and achievement of national goals for climate and environment.

In the traditional credit scoring method, the statistical model estimates the possibility of default based on financial and socioeconomic data such as financial ratios, historical payment patterns, and demographic profile attributes [22-24]. These models work for traditional borrowers but have a number of limits when it comes to green initiatives for the following reasons:

- ESG criteria is ignored: These traditional models do not consider social and environmental factors that are important in establishing the sustainability of a project.
- Subjective bias: Green initiatives, although promising, may be penalized in review due to subjective judgment brought in by creative or unusual projects.
- Ignoring regulatory and reputational issues: Traditional models cannot capture the complexity of risks related to social reputation and environmental regulations, which reduces the quality of financing decisions.

All the above-mentioned disadvantages demonstrate the need to transition to more reliable methods that can combine financial and non-financial data and adjust the evaluation

to allow for unique characteristics of green projects, thus opening avenues for the use of AI and ML technology [25, 26].

2.3 Application of AI and ML to green credit scoring

Applying artificial intelligence and machine learning to green credit scoring overcomes some of the limitations of traditional models [8, 26]. Indeed, the AI and ML system can process ESG and financial data simultaneously, find more complicated nonlinear relationships, and generate more precise and flexible forecasts [9, 13, 22, 27, 28]. The key potential aspects include:

- Less human bias: Projects are assessed against objective standards by algorithms, which reduces subjective assessment.
- Adaptability to new data and regulations: Machine learning models are able to adjust for new trends and regulatory changes to provide green ratings that become more and more accurate.
- Diversification: Ability to assess projects that are offbeat or innovative and, in particular, those that have profitability that is delayed, which the conventional models cannot capture.

It has been shown that behavioral factors play an important role in the adoption of AI and ML technologies in green scoring. According to the Technology Acceptance Model, two major variables come into play for the intention of adopting a technology, namely:

- Perceived usefulness: The perception that the technology improves performance in the targeted task. In green scoring, this equates to improving the accuracy and fairness of credit decisions.
- Perceived ease of use: The degree to which the user thinks that it is easy to use and discern the tool.

Unified Theory of Acceptance and Use of Technology extends these factors through stating that the approval of technology depends on the effects of performance expectancy, social impact and facilitating conditions [29]. At the same time, behavioral finance and Prospect Theory explain that financial decision-makers are subject to cognitive biases, such as aversion to algorithms, overestimation of risk, or aversion to uncertainty, which can hinder the adoption of AI/ML systems even when their performance is proven [30]. In addition, several studies highlight that organizational trust is a key determinant in the adoption of AI/ML systems. It refers to the perception of reliability, predictability, and security of algorithmic recommendations.

2.4 Theoretical framework and Conceptual model

The use of AI and ML systems in green credit scoring is the result of a complicated interaction of organizational, behavioral, and technological elements. The reasons why Moroccan bank decision-makers choose to adopt or reject these technologies need to bring together many theoretical views that can capture both human cognition and the larger organizational context.

The Technology Acceptance Model (TAM) [29] - a widely used theory explaining individual acceptance of technology - provides one core lens for understanding the cognitive assessment of new technologies. According to this approach, the decision-makers' perceived utility of AI/MLs derives from their opinions that these systems improve the precision, effectiveness, and fairness of green credit scoring. In a similar way, perceived ease of use measures the level to which AI/ML products are considered easy and effortless for users to work with. In TAM, these two perceptions directly impact the intention to adopt a technology and are therefore predictive of actual adoption. Although TAM provides a rich explanation

of individual evaluation procedures, it falls short in accounting for organizational contingencies or psychological biases, especially relevant when adopting automated scoring systems in situations where risk and uncertainty perceptions are widespread.

To surmount these constraints, this study combines Prospect Theory with notions of behavioral finance. Algorithm aversion, loss aversion, and overestimation of technological danger are various cognitive biases that may result in people being less likely to adopt even when AI/ML systems outperform technically [31, 32]. This, therefore, calls for the need to be psychologically considerate along with cognitive assessment. This study provides a richer insight into resistance that falls outside the traditional TAM by conceptualizing behavioral biases as elements that negatively impact the intention to adopt.

The adoption process is also heavily reliant on the transparency and explainability of AI/ML systems [33, 34]. Algorithmic transparency improves decision-makers' understanding on how the AI derives its conclusions, via the Explainable AI literature and technological adoption trust frameworks [35]. This ultimately builds trust in the AI recommendations, which is essential to move past ambiguity and behavioral resistance. As a result, trust fills an important mediating role in the intersection of intention to adopt and technology-based factors of AI/ML systems. However, adoption intention does not always equal usage. The transformation of intention to action is explained in the Theory of Planned Behavior (TPB) by Ajzen [32]. Perceived behavioral control-the belief that one has the required abilities, resources, and organizational support- serves to mediate the relationship between adoption intention and adoption to determine intention to use AI/ML in green credit scoring.

Finally, the outcomes of the adoption process are influenced by the institutional and organizational contexts [35, 36]. Institutional Theory posits that organizational values, regulatory coalitions, and pledges to sustainability shape behaviors around technology adoption. This theory assumes that commitment to environmental concerns will moderate the effect of intention on actual adoption, reflecting the degree of priority that banks assign to sustainability objectives and ESG commitment. This puts the model also in the context of the bigger organizational and societal context that AI/ML adoption takes place alongside individual and cognitive variables being able to form a richer understanding of the AI/ML adoption process.

Table 1. Research Variables.

Variable	Nature	Description / Role
Perceived Usefulness (PU)	Independent	The extent to which decision-makers believe AI/ML enhances accuracy, efficiency, and objectivity in green credit scoring.
Perceived Ease of Use (PEOU)	Independent	The degree to which AI/ML systems are user-friendly, easy to understand, and require minimal effort, facilitating adoption.
Algorithmic Transparency (EXPL)	Independent	Extent to which AI/ML decision-making processes are understandable and explainable, reducing uncertainty.
Behavioral Biases (BIAS)	Independent	Cognitive distortions such as algorithm aversion, loss aversion, or fear of uncertainty that negatively affect adoption intention.
Trust in AI (TRUST)	Mediating	Confidence in AI/ML outputs; mediates the effect of transparency on adoption intention.
Adoption Intention (INT)	Mediating / Dependent	The willingness or plan of decision-makers to adopt AI/ML systems; mediates between determinants and actual adoption.
Actual Adoption (AAI)	Dependent	The real implementation and use of AI/ML in green credit scoring practices.

Environmental Commitment (EENG)	Moderating	Organizational sustainability engagement; strengthens the translation of adoption intention into actual adoption.
Perceived Behavioral Control (PBC)	Moderating	It reflects both the bankers' perceived technical competence and the availability of organizational resources (e.g., data infrastructure, training, and management support) necessary to adopt and effectively use AI/ML systems in green credit scoring.

The following conceptual model shall help in analyzing how different determinants ranging from Cognitive and Technology Evaluation to Behavioral and Institutional factors impact the adoption of AI- and ML- based models in green credit scoring within the Moroccan banking sector.

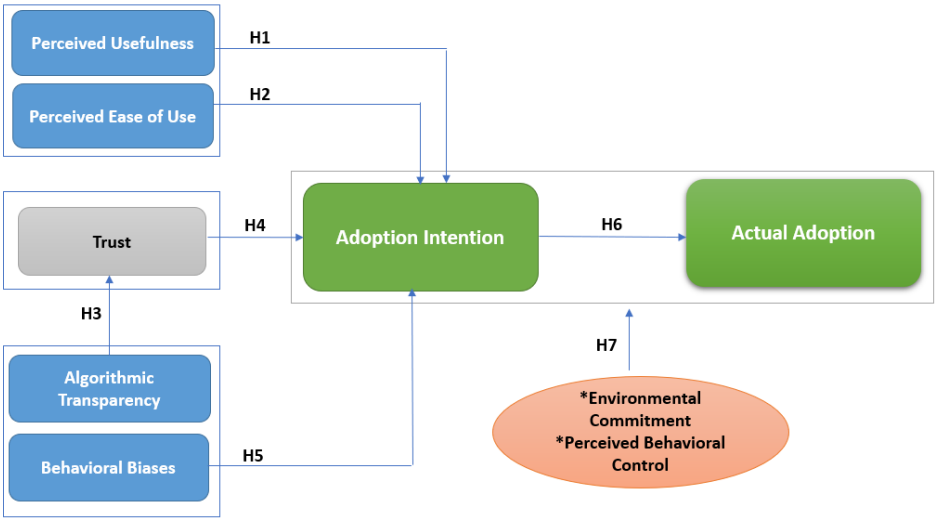

Fig. 1. Conceptual Model Diagram

From the conceptual model above, key hypotheses are being put forward as follows:

- H1: The perceived usefulness of AI/ML in green credit scoring positively influences adoption intention.
- H2: The perceived ease of use of AI/ML in green credit scoring positively influences adoption intention.
- H3: Algorithmic transparency positively affects trust in AI/ML based models in green credit scoring.
- H4: Trust in AI/ML in green credit scoring mediates the relationship between algorithmic transparency and adoption intention.
- H5: Behavioral biases negatively impact adoption intention of AI/ML in green credit scoring.
- H6: Adoption intention positively predicts actual adoption of AI/ML in green credit scoring.
- H7: Environmental commitment and Perceived behavioral control moderate the relationship between adoption intention and actual adoption of AI/ML in green credit scoring.

3 Methodology

This research design follows a hypothetico-deductive approach that enables testing the conceptual model based on the theoretical framework mentioned above. This will help to identify the behavioral and organizational factors that may affect the adoption of AI and ML systems applied to green credit scoring. A mixed approach is chosen due to the complexity of the phenomenon studied. On one hand, the qualitative dimension allows going deeper into perceptions, resistance, and organizational levers that a questionnaire cannot capture. The quantitative dimension, on the other hand, allows us to empirically test the relationships between the variables in the model and verify the statistical robustness of the hypotheses. Thus, this methodology will ensure triangulation and reinforce the validity of the current study.

3.1 Qualitative Methodology

3.1.1 Participants and study context

Based on their knowledge or direct participation in the field of our study, 15 participants in the Moroccan banking sector have been chosen taking into consideration their experience with green credit scoring and their engagement in strategic decisions. They include:

- 5 Credit managers;
- 4 Risk analysts;
- 3 CSR/ESG and green finance managers;
- 3 Data analysts and data scientists working on AI/ML projects.

The interviews lasted an average of 75 minutes. They took place in Agadir, Casablanca, and Rabat between March and April of 2025. The qualitative analysis was conducted thematically and deductively, in direct relation to hypotheses from H1 to H7.

The qualitative phase enables a better understanding of perceptions and behaviors of decision-makers towards AI/ML systems used in green credit scoring. First, the semi-structured interviews provide a deep comprehension of the concepts of resistance and reluctance regarding the adoption of AI- and ML- based models in green credit scoring. Second, they help identifying the cognitive, behavioral and organizational factors that have an impact on adoption intention and actual adoption. They also underline managerial levers for responsible adoption.

3.1.2 Data collection and processing

At the beginning of the process, the semi-structured interview guide was tested on a pilot sample of 04 participants from the banking sector to verify the clarity of the questions, the relevance of the topics, and the duration of the interviews. This step allowed us to reformulate certain questions on algorithm transparency and introduce concrete examples of green scoring. The test confirmed that the guide was appropriate for exploring behavioral perceptions and the adoption of AI and ML in green credit scoring. Subsequent data collection and analysis were conducted iteratively, and thematic saturation was observed from the 11th interview onward, with no substantively new themes emerging in the remaining interviews, which were conducted to confirm saturation. The semi-structured interview guide was organized around four major thematic layers, each designed to explore a distinct dimension of the adoption of AI/ML systems in green credit scoring:

-Cognitive / Technology Evaluation Layer: This layer addressed respondents' perceptions and evaluations of the technological characteristics of AI and ML tools.

- Behavioral Layer: This dimension explored individual and psychological determinants influencing adoption decisions.

-Institutional Layer: This layer examined the organizational and environmental context that supports or constrains AI/ML adoption.

-Intention-to-Action Layer: This final dimension focused on the transition from expressed intention to actual implementation of AI/ML systems.

3.2 Quantitative Methodology

3.2.1 Population and Sampling

The targeted population is composed of 120 stakeholders in the Moroccan banking industry who are directly involved in green credit. The selection include:

- 36 Credit managers;
- 28 Risk analysts;
- 30 CSR/ESG and green finance managers,
- 26 Data analysts and data scientists working on AI/ML projects.

The sample selection is done through non-probability convenience sampling, prioritizing those subjects whose work experience is directly related to scoring tools or sustainable financing projects. The quantitative phase involved 120 respondents. The sample size is relevant regarding the methodological recommendations of analyses by means of PLS-SEM, which require a number of participants proportional to the number of estimated parameters [37], assuring sufficient statistical robustness in order to detect the mediating and moderating effects.

Table 2. Socio-demographic profile of respondents (n=120)

Characteristics	Terms	Percentage
Gender	Male/Female	40% / 60%
Age	25-34 / 35-44 / 45-54 / 55+	20% / 40% / 35% / 5%

Work Experience	<5years / 5-10 years / >10 years	24% / 37% / 39%

3.2.2 Data Collection and processing

Quantitative data were collected from 120 professionals using a structured questionnaire. They were analyzed using SmartPLS 4 software, which allowed us to verify reliability and validity and test the structural relationships between variables in accordance with the conceptual model. This phase was conducted as follows:

- Qualitative themes coded into quantitative items on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree) in order to generate data appropriate for the PLS-SEM method.
- Pilot pre-test on 20 respondents to check the validity and consistency of the items.
- Online administration of questionnaire in May-August 2025.

Ethical considerations, including informed permission, confidentiality and anonymity, and the right to withdraw, were important in the interviews.

The collected data were analyzed using SmartPLS 4, which featured the following:

-Descriptive statistics showed a summary of the central tendency and dispersion of the variables measured: The average score that the respondents recorded for each variable was the mean, on a 5-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. The standard deviation (SD) represents the variability in responses. The smaller the SD, the stronger the agreement among the responders, and vice versa.

-Correlation Analysis which states that Pearson correlation coefficients (r) measure the direction and the strength of linear relationships between variables:

- r = +1: Perfect positive correlation; as one variable increases, so does the other.
- r = -1: Perfect negative correlation; as one variable increases, the other decreases.
- r = 0: No linear correlation.

4 Results

4.1 Qualitative Analysis

The transcripts were subjected to methodical theme coding using the NVivo program. This approach enabled the detection of emerging categories, repeating patterns, and verification of data saturation-that is, the main themes became repetitive after the tenth interview. The study of the fifteen semi-structured interviews with Moroccan banking staff led to the detection of a number of interrelated themes that influence the use of AI/ML for green credit scoring. Three overall themes and their respective sub-themes showed a clear connection between intention and actual adoption: Perceived Value and Practical Benefits, Trust and Explainability, and Cognitive and Institutional Dynamics.

Table 3. Thematic Synthesis of Qualitative Findings.

Main Theme	Sub-Themes	Illustrative Quotes	Interpretation / Theoretical Link
1. Perceived Value and Practical Benefits	**1.1 Accuracy and Objectivity**	"ML helps us evaluate innovative projects that traditional methods would have missed. It	Highlights the perceived usefulness of AI/ML through improved accuracy and objectivity in decision-making.

		makes scoring more reliable and fair."	
	1.2 Efficiency and Strategic Support	"With ML, we can quickly assess dozens of projects while ensuring ESG criteria are fully considered."	Confirms that perceived usefulness enhances adoption intention by demonstrating efficiency and strategic alignment.
2. Trust and Explainability	**2.1 Algorithmic Opacity and 'Black Box' Concerns**	"Even if the model is accurate, some managers are hesitant because they don't understand why a project is classified as risky."	Lack of algorithmic transparency generates skepticism and limits trust in AI/ML-based recommendations.
	2.2 Confidence Through Transparency	"When the system explains its reasoning clearly, managers feel comfortable using it."	Transparency builds trust, confirming the mediating role of trust between transparency and adoption intention.
3. Cognitive and Institutional Dynamics	**3.1 Behavioral Resistance and Biases**	"AI can make better decisions than humans, but we are afraid of giving up control over important approvals."	Reflects behavioral biases such as loss aversion and fear of automation, reducing adoption intention.
	3.2 Organizational Support and Environmental Commitment	"Green projects are complex to evaluate. In our bank, AI is a tool to make ESG compliance effective rather than a threat."	Demonstrates that environmental commitment and supportive culture Foster AI/ML adoption.
	3.3 Regulatory Context	"Regulators expect banks to consider ESG criteria; AI helps us comply efficiently, but we need clear guidance."	Underlines institutional pressure and legitimacy-seeking behavior consistent with Institutional Theory.
	3.4 Perceived Behavioral Control (PBC) and Actual Adoption	"We want to use ML, but some teams lack the training and time to implement it fully. When support is available, intention quickly turns into action."	Confirms that perceived behavioral control moderates the link between intention and actual adoption (TPB).

In summary, the qualitative data show that adoption is multi-dimensional:

- Perceived usefulness and ease of use increase intention.
- Trust, mediated by transparency, reinforces adoption intention.
- Behavioral biases act as barriers.
- Institutional and regulatory support facilitate actual adoption.
- Perceived behavioral control explains why intention sometimes does not immediately translate into action.

4.2 Quantitative Analysis

The analysis of 120 respondents in the Moroccan banking sector indicates a generally positive disposition towards the adoption of AI/ML in green credit scoring.

Table 4. Descriptive Statistics.

Variable	Mean	SD
Perceived Usefulness (PU)	4.35	0.46
Perceived Ease of Use (PEOU)	3.78	0.58
Trust in AI (TRUST)	3.97	0.52
Transparency (EXPL)	3.44	0.65
Behavioral Biases (BIAS)	3.10	0.68
Adoption Intention (INT)	4.20	0.48
Environmental Commitment (EENG)	4.08	0.44
Perceived Behavioral Control (PBC)	4.05	0.42
Actual Adoption (AAI)	3.95	0.50

Table 5. Correlation analysis.

Relationship	r	Interpretation
PU → INT	0.72	Strong positive effect of perceived usefulness on intention
PEOU → INT	0.56	Moderate positive effect of ease of use on intention
TRUST → INT	0.70	Trust strongly supports adoption intention
EXPL → TRUST	0.63	Transparency enhances trust
BIAS → INT	-0.47	Biases reduce intention to adopt
EENG → INT	0.59	Higher environmental commitment increases adoption intention
PBC → INT	0.62	Higher perceived behavioral control increases adoption intention
INT → AAI	0.68	Strong translation from intention to actual adoption

The relationships between constructs confirm the key determinants and moderating effects proposed in the conceptual model:

- Perceived Usefulness (PU) received the highest mean (M = 4.35, SD = 0.46) indicating that decision-makers recognized the considerable advantages AI/ML brings to the accuracy, efficiency, and objectivity of green credit evaluation.
- Perceived Ease of Use (PEOU) was moderate (M = 3.78, SD = 0.58), indicating that while AI/ML systems are generally perceived as manageable, operational complexity cannot be ruled out.
- Trust in AI (TRUST) received a high score (M = 3.97, SD = 0.52), which showed that while participants tended to trust the outputs from AI/ML, there is still some level of caution.
- Transparency (EXPL) indicates a moderate score (M = 3.44, SD = 0.65) which indicates some level of AI decision-making processes partially understood inhibits full trust.
- Behavioral Biases (BIAS) were rated moderate (M = 3.10, SD = 0.68) which indicates there are ongoing concerns based on algorithm aversion or fear of loss of control.
- Adoption Intention (INT) was high (M = 4.20, SD = 0.48) showing decision-makers are to a large extent willing to incorporate AI/ML systems into their green credit practice.
- Environmental Commitment (EENG) received a high scoring (M = 4.08, SD = 0.44) which suggests institutions have sustainably embedded in their strategies.
- Perceived Behavior Control (PBC) was high (M = 4.05, SD = 0.42) showing that a higher sense of control increases the likelihood of actual adoption of AI/ML models in green credit scoring.

- Actual Adoption (AAI) was relatively high (M = 3.95, SD = 0.50) indicating that AI/ML tools are increasingly adopted in practice.

In addition, the correlation analysis confirmed the following statements:
-PU → INT (r = 0.72): Perceived usefulness is a strong predictor of intention to adopt.
-PEOU → INT (r = 0.56): Perceived ease of use has a positive influence on intention to adopt.
-TRUST → INT (r = 0.70): Trust is a significant driver of intention to adopt.
-EXPL → TRUST (r = 0.63): Higher levels of transparency lead to an increase in trust, therefore supporting the proposed mediating relationship of trust.
-BIAS → INT (r = -0.47): Behavioral biases negatively influence intention to adopt and
-EENG → INT (r = 0.59): A commitment to the environment positively influences intention to adopt.
-PBC→ INT (r = 0.62): A higher perceived behavioral control positively influences intention to adopt.
-INT → AAI (r = 0.68): Having a strong correlation signifies that intention will lead to the action of adoption is acceptable.

The results indicate that perceived usefulness and trust are the primary drivers of adoption intention, while behavioral biases and limited transparency moderate adoption. Importantly, perceived behavioral control influence the translation of intention into actual adoption, supporting the relevance of TPB in our framework. Environmental commitment further reinforces adoption but with a moderate effect.

5 Discussion

This research focused on organizational, technological, and behavioral factors in order to assess the usage of artificial intelligence and machine learning in green credit scoring. The discussion of results was based on insights provided by both qualitative analysis -semi structured interviews- and quantitative analysis -a questionnaire answered by 120 professionals- in order to derive complex and contextualized conclusions about the Moroccan banking industry.

5.1 Perceived Usefulness & Perceived ease of use and AI/ML Adoption in green credit scoring

H2 is confirmed by the somewhat positive connection between perceived ease of use (M = 3.78, SD = 0.58) and adoption intention (r = 0.56). Although people recognize the technological advantages of machine learning, some complexity and learning effort are still obstacles. According to interviews, decision-makers require training and user-friendly interfaces in order to feel comfortable utilizing ML solutions. "Some of the models are powerful, but understanding how to operate them efficiently takes time and guidance," a data analyst clarified. This bolsters the TAM claim that by lowering cognitive burden and boosting confidence, ease of use promotes adoption.

Moreover, ML's perceived utility is relatively high (M = 4.35, SD = 0.46) and is strongly correlated with adoption intention (r = 0.72), which is supportive of H1. This pattern suggests that financial decision-makers are aware of the potential of machine learning to enhance the precision, efficiency, and objectivity of green scoring. This was also corroborated through qualitative interviews analyzed with NVivo software. Specifically, the respondents mentioned the possibility of processing financial and ESG data jointly, discovering nonlinear patterns, and reducing the impact of human judgment. "ML helps us to identify risks that

might have been missed using traditional methods," a risk manager said. It enhances impartiality and dependability in scoring.

Thus, the convergence of quantitative and qualitative data supports the Technology Acceptance Model's premises that perceived utility plays a critical role in influencing technology adoption. Results support other prior research findings, such as that of Fuster et al. [11], that AI-based integration of ESG variables significantly enhances evaluation of green initiatives, particularly the highly innovative ones which become profitable after a certain amount of time. From this perspective, with respect to performance and long-term compliance of financial players, perceived usefulness is considered a strategic lever rather than a technological advantage.

5.2 Algorithmic Transparency and Trust

Algorithmic transparency shows a moderate mean (M = 3.44, SD = 0.65) and is positively correlated with trust in AI (r = 0.63), confirming H3. Trust in AI itself has a strong correlation with adoption intention (r = 0.70), confirming H4 and highlighting its mediating role. Indeed, qualitative analyses with NVivo pointed out several main themes: lack of comprehension of algorithmic decisions, fear of opacity ("black box") and the importance of clear explanations. For instance, one data scientist said, "Even if the model is accurate, some managers have a hard time understanding why a project is classified as risky, which slows down the adoption." These results are consistent with the previous works on the role of XAI in building trust and decreasing algorithm aversion in a professional setting.

Therefore, the discussion has shown that transparency and trust mediation are not only technical l considerations but also a means of maintaining the psychological disposition of a decision-maker regarding the integration of AI/ML into green scoring practices. Institutions that invest in XAI frameworks and user training increase the adoption and credibility of their models.

5.3 Behavioral Biases

Behavioral biases (M = 3.10, SD = 0.68) are negatively associated with adoption intention (r = -0.47), confirming H5. Decision-makers report concerns over loss of control, over-reliance on automation, and fear of algorithmic errors. In the interviews, it became evident that mistrust in algorithms is caused by a perceived loss of control and uncertainty regarding automated decisions. One green finance manager said: “We want to keep control over important decisions. AI can help, but it's hard to trust it completely.” These findings are supported by the Prospect Theory of Kahneman & Tversky [30], who also established that users would reject or modify even better performance of recommendations by automated systems. These results point out that AI/ML's adoption does not rely merely on technological performance: it is strongly psychological and organizational cultural.

5.4 Adoption Intention to Actual Adoption

Hypothesis 6 is supported by the change from intention to actual adoption (M = 3.95, SD = 0.50; r = 0.68 between INT and AAI). According to interviews, organizational preparedness, infrastructure, and perceived control all influence the actual adoption of machine learning, even when managers are eager to adopt it: A data scientist said, "We plan to use ML models, but resources and proper integration take time." This behavior is

explained by the Theory of Planned Behavior: as Ajzen himself wrote in 1991, "For people to act on their intentions, favorable conditions are needed." [38].

Indeed, environmental commitment and perceived behavioral control moderate adoption intention and actual adoption, respectively, thus partially supporting H7. Quantitative correlations indicate that stronger ESG integration and regulatory compliance are related to a higher likelihood of actual ML implementation. As interviews showed, banks already involved in ESG practices view AI as a means to enhance compliance and the efficiency of green financing decisions. As confirmed by a risk manager: "Green projects are more complex to evaluate; AI helps us make decisions aligned with our ESG commitments and regulations."

These results confirm that the institutional context and organizational culture moderate the relationships between perceived usefulness, trust, and adoption. Institutions that have a digital culture and a strong commitment to sustainability are more likely to adopt ML; this is consistent with the results of Venkatesh [29] regarding the role of organizational influence in the adoption of technologies.

To sum up, the development of both the quantitative and qualitative results highlight a unique statement: the use of artificial intelligence and machine learning for green scoring balance institutional backing, trust and understanding from people, and performance of the technology. While it is generally understood that AI/ML models are seen as pragmatic, actionable models, the behavioral aversion and lack of transparency still stops it from being a commonplace model. Qualitative themes validate and expand on the quantitative themes by providing specific examples of user complaint and acceptance lever. In essence, the above discussion outlined three key needs for AI/ML to be successfully implemented in a green scoring context: 1) a technical dimension that creates fair and accurate results; 2) explainability and trust mediation to reduce behavioral biases; and 3) alignment with institutional values and compliance with relevant legislation. In addition to contributing to the literature on TAM in the realm of sustainable finance and behavioral finance, this integrated approach also provides concrete implications for institutions that are willing to use AI responsibly.

Findings of the study align with and expand upon existing literature in several ways. To cite the first example, in similarity to Fuster et al. [11], the perceived usefulness of AI/ML technology in the evaluation of green initiatives is supported in the study because of the critical influence that perceived usefulness wields in the adoption of the technology, in cases that call for complex analysis in terms of ESG [39]. Moreover, the importance of transparency and trust that this study attempts to highlight does indeed align with the work completed in the field of Explainable AI (XAI) in financial decision-making tasks [40]. The work of Kahneman and Tversky [30] and recent studies of automation bias [17, 41, 42] further support the behavioral biases identified in our research, as these note that even highly precise ML models may experience resistance if decision-makers perceive a loss of control. Last but not least, the findings concerning organizational culture and ESG alignment support Venkatesh et al.'s work on technology adoption, since a commitment to environmental issues is revealed as a moderating variable for the intention-behavior gap in the adoption of AI/ML. To put our results into this larger body of literature, it also becomes clear that the effective adoption of AI/ML in green credit scoring does not depend on technical performance alone but also on aspects relating to behavior, culture, and institution-a many-faceted point of view reinforcing and further enhancing earlier studies.

6 Conclusion

In this research, the factors which impact green credit scoring through machine learning in the Moroccan banking system have been analyzed by blending behavioral, technological, and

institutional views. Using a combination of qualitative and quantitative techniques, in which 120 banking professionals have been interviewed, along with qualitative information gathered through in-depth interviews and analyzed with NVivo software, this paper has gained in-depth insights into behavior shaping the adoption and adoption intentions of artificial intelligence and machine learning-based systems in sustainable finance practices.

The results prove that the primary hypothesis of the TAM in this original scenario is correct. “Overall perceived usefulness is a far more important factor than other variables in determining adoption.” Based on decision-makers' views, AI/ML increases the precision, efficiency, and impartialness of green credit ratings. Moreover, “when several different ESG variables need to be combined in a credit rating decision,” this enhancement is even greater. Although technical complexity is a moderate barrier, ease of use is a significant factor in fostering adoption because it “can contribute to greater confidence in day-to-day operations and can reduce 'mental' or cognitive overload.” Algorithmic transparency and explainability help in building trust. This “lies between an understanding and adoption intention.” The presence and influence of openness “can contribute to attitudes toward behaviors in two different ways”: Firstly, “overcome aversion to algorithms/algorithms' aversion.” Secondly, this factor “contributes directly to a trust in decisions made by an automation system as opposed to trust in decisions' technical attributes.” The presence and significance of behavioral biases like “fear of automation and loss of control” pointed toward psychological and cultural aspects surrounding technology adoption. At the organizational level, environmental commitments and regulatory imperatives seem to hasten the journey from intention to successful implementation. In addition, financial institutions that actively seek sustainability initiatives and successfully integrate ESG factors are also more likely to deploy ML technologies in practice; therefore, alignment within institutions and readiness at the organizational level seem to be the prerequisites for technology adoption.

Beyond performance-oriented analyses, recent research has begun to explore the application of artificial intelligence and machine learning in sustainability-oriented financial decision-making [43]. In this regard, studies on AI-driven green credit scoring highlight both the operational benefits of machine learning—such as improved accuracy, efficiency, and ESG data integration—and the behavioral and institutional challenges that condition their adoption. Issues related to trust, algorithmic transparency, perceived usefulness, and resistance to automation emerge as critical factors shaping decision-makers’ acceptance of these systems, particularly in emerging banking contexts. This line of research extends the AI and business performance literature by emphasizing the role of human–algorithm interaction in responsible and sustainable finance.

Theoretically, this study expands the application of Technology Acceptance Model to sustainable finance by adding institutional theory that captures contextual and regulatory effects, and behavioral finance components explaining resistance mechanisms. In such a way, this multi-theoretical contribution develops a more sophisticated framework when studying decision-making in sustainability-oriented innovation and increases knowledge about AI and ML uptake in emerging markets. From a management perspective, the study findings emphasize the need for financial institutions to engage in training of users to decrease complexity and augment trust, to increase algorithm transparency through the use of explainable AI frameworks, and to validate the perceived value of machine learning (ML) tools. In addition, ML projects also need to adhere to ESG policies and legal requirements to develop and deploy responsibly, fairly, and consequentially. Future research could consider the role of this analytical framework applied to other developing economies, financial domains, longitudinal studies to document the evolution of adoption behavior, and the prospective experiences of explainability mechanisms to enhance trust in users. Although performance assessments of ML scoring systems may be useful to estimate their effectiveness

and strategic value, other behaviors and organizational dimensions could contribute to our understandings of AI diffusion.

Ultimately, our research demonstrates that the effective integration of machine learning into green credit scoring must involve a moderation of innovation, organizational commitment and human acceptability, rather than purely technical competency. The study re-iterates this moderation to potentially inform a conceptual and practicable pathway to generate a more transparent, more inclusive, and more sustainable green financing ecosystem in Morocco and similar emerging contexts. Furthermore, this study has several limitations that suggest avenues for future research. First, it focuses exclusively on the Moroccan banking sector, which may limit the generalizability of the findings to other emerging markets or financial domains. Second, the cross-sectional design captures adoption behavior at a single point in time, making it difficult to assess long-term changes in attitudes or practices. Future research could address these gaps by conducting longitudinal studies, applying the framework to other regions or industries, evaluating the performance and strategic impact of ML models, and exploring additional organizational and behavioral factors such as leadership support, interdepartmental collaboration, or risk tolerance that may shape AI/ML adoption in green finance.

References

1. OECD, *Global Outlook on Financing for Sustainable Development 2023: No Sustainability Without Equity* (OECD Publishing, Paris, 2022)
2. Ministère de la Transition Énergétique et du Développement Durable, *Stratégie nationale de développement durable 2030* (Gouvernement du Maroc, Rabat, 2017)
3. A. Bouchta, S. E. Alaoui, *Int. J. Econ. Stud. Manag.* **4**, 4 (2025)
4. A. Hassanein, H. Tharwat, Artificial Intelligence (AI) and Green Finance, in *The Palgrave Handbook of Green Finance for Sustainable Development* (Springer, Cham, 2024)
5. Z. Li, P. Chen, *Sustainability* **16**, 7901 (2024)
6. A. Bahbah, F. Touhami, *Rev. Econ. Financ.* **21**, 2149–2159 (2023)
7. P. Giudici, L. Wu, *Front. Artif. Intell.* **8**, 1566197 (2025)
8. N. Kuznietsova, R. Amoroso, An approach to green financial credit risks modeling, in *Proc. XXI Int. Sci. Pract. Conf. Inf. Technol. Secur. (ITS-2021)*, CEUR Workshop Proc. **3241** (2021)
9. K. Fotova-Cikovic, V. Cvetkoska, D. Primorac, *J. Risk Financ. Manag.* **18**, 420 (2025)
10. J. O. Omotoso, A.-K. Elfredah, O. T. Jesu-Okiki, S. Dare, O. Fagbohun, *J. Artif. Intell. Mach. Learn. Data* **1**, 3 (2025)
11. A. Fuster, P. Goldsmith-Pinkham, T. Ramadorai, A. Walther, *J. Finance* **77**, 5–47 (2021)
12. C. Wang, R. Nazar, S. Ali, M. S. Meo, *Technol. Soc.* **83**, 102960 (2025)
13. Y. Wang, J. Feng, R. Shinwari, E. Bouri, *J. Environ. Manage.* **360**, 121212 (2024)
14. N. Kuehl, M. Goutier, R. Hirt, G. Satzger, arXiv:2004.04686 (2020)
15. T. M. Mitchell, *Machine Learning* (McGraw-Hill Science/Engineering/Math, New York, 1997)
16. G. Ola, J. Tyler, J. Nelson, *Introduction to Supervised Learning* (Springer, Cham, 2025)
17. J. Zhang, Q. Liu, S. Yang, *Sustainability* **17**, 10759 (2025)
18. S. Mestiri, *Data Sci. Financ. Econ.* **4**, 236–248 (2024)
19. M. Schmitt, arXiv:2402.03806 (2024)
20. N. Nhung, P. Thao, *Middle East Res. J. Econ. Manag.* **5**, 1–7 (2025)

21. H. Wang, M. Liu, *Sustainability* **17**, 1590 (2025)
22. P. Golbayani, I. Florescu, R. Chatterjee, arXiv:2007.06617 (2020)
23. L. C. Thomas, D. B. Edelman, J. N. Crook, *Credit Scoring and Its Applications* (SIAM, Philadelphia, 2002)
24. L. Thomas, J. Crook, D. Edelman, *Credit Scoring and Its Applications, Second Edition* (SIAM, Philadelphia, 2017)
25. S. Ramzani, P. Konhaeusner, O. Olaniregun, A. Abu-Alkheil, N. Alsharari, *Eur. J. Bus. Manag. Res.* **9**, 43–55 (2024)
26. J. Omotoso, E. Kevin-Alerechi, O. Okiki-Jesu, D. Sunday, O. Fagbohun, S. Olanrewaju, *J. Artif. Intell. Mach. Learn. Data Sci.* **3**, 2346–2352 (2025)
27. V. Cvetkoska, K. Fotova-Cikovic, M. Tasheva, *Mathematics* **9**, 1597 (2021)
28. Y.-S. Lee, H.-S. Shih, *Int. J. Inf. Manag. Sci.* **26**, 103–122 (2015)
29. D. Marikyan, S. Papagiannidis, Unified Theory of Acceptance and Use of Technology: A review, in *TheoryHub Book*, S. Papagiannidis (Ed.) (Newcastle University, Newcastle, 2025)
30. D. Kahneman, A. Tversky, *Econometrica* **47**, 263–291 (1979)
31. B. Dietvorst, J. Simmons, C. Massey, *Manag. Sci.* **64**, 1155–1170 (2018)
32. I. Ajzen, *Attitudes, Personality, and Behavior*, 2nd ed. (Open University Press/McGraw-Hill, Maidenhead, 2005)
33. M. Buecker, G. Szepannek, A. Gosiewska, P. Biecek, arXiv:2009.13384 (2020)
34. G. Vilone, L. Longo, arXiv:2006.00093 (2020)
35. T. Bitzer, M. Wiener, W. A. Cram, Algorithmic transparency: concepts, antecedents, and consequences: a review and research framework, *Commun. Assoc. Inf. Syst.* **52**, 293–331 (2023)
36. O. Berthod, Institutional theory of organizations, in *Global Encyclopedia of Public Administration, Public Policy, and Governance*, A. Farazmand (Ed.) (Springer, Cham, 2022)
37. J. Hair, A. Alamer, *Res. Methods Appl. Linguist.* **1**, 100027 (2022)
38. I. Ajzen, *Organ. Behav. Hum. Decis. Process.* **50**, 179–211 (1991)
39. Q. Gong, J. Gu, Z. Kong, S. Shen, X. Dong, Y. Li, C. Li, *Sustainability* **17**, 5942 (2025)
40. C. Hurlin, C. Perignon, *Rev. d'Econ. Financ.* **135**, 21–50 (2019)
41. S. Alshammari, M. S. Rosli, A review of technology acceptance models and theories, *Int. J. Recent Technol. Eng.* **4**, 12–22 (2020)
42. H. Choung, J. S. Seberger, P. David, *Int. J. Hum.-Comput. Interact.* **40**, 7451–7468 (2024)
43. A. Moumen, *Morocc. J. Quant. Qual. Res.* **7**, 54770 (2025)