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The Adoption of Artificial Intelligence as a Lever for Rationalizing Financial Decision-Making: An Analysis of Its Influence on Behavioral Biases, Risk Management, and Decision-Making Performance in the Moroccan Banking Sector

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Abstract. In financial decision making, bank professionals' bounded rationality in making decisions and their confirmation, over-confidence and anchoring judgment lead them to make financial choices in banks. This research is designed to find out whether Artificial Intelligence (AI) can help with rationalizing the decisions and how it can be used for that. Multiple regression was used to analyze a survey of 200 professionals in the Moroccan commercial, participative and investment banks and asset management companies as well as 5,000 bootstrap resamples for estimating the parallel mediation model. The level of adoption of AI is positively correlated with the perceived bias control and risk management capability and the perceived decision rationality ($p<0.001$). The overall model explains 67.3% of the variance in the decision making performance. Decision rationality is the dominant channel (indirect effect = 0.332; 95% CI [0.238; 0.432]), followed by risk management (0.157) and bias control (0.053). The three mechanisms jointly account for 65.3% of the total effect of the adoption of AI, and a significant direct effect remains. But the debiasing effect of AI is the weakest link – it's essential to rationalist banking decisions by structuring the decision process and improve risk assessment. The results have implications in the field of AI governance in Moroccan banks and for the supervisory authorities.
Keywords: *Artificial Intelligence, Behavioral Biases, Decision-Making Performance, Mediation Analysis, Moroccan Banking Sector, Risk Management.*

1. Introduction

Making a series of decisions without certainty, decisions which relate to a decision to lend to somebody, to price the risk which they were taking, to keep a particular asset, or to reduce a risk – that's the most basic forms of banking. In classic finance, it is assumed that there is a rational decision maker, who may be an optimizer, but Simon (1955) had introduced bounded rationality, where bounded rationality is caused by lack of information, cognitive ability and time. Later behavioral finance commented on the frequency of the errors. Tversky and Kahneman (1974) came up with the ideas of the heuristics of representativeness, availability and anchoring; Kahneman and Tversky (1979) showed that losses are more weighty than equivalent gains; Odean (1998) and Barber and Odean (2001) showed that overconfident investors trade too much and destroy value. These biases don't only impact the retail investor. The same cognitive weaknesses are built into the credit officer, analysts, risk manager and the impact of the size of the balance sheet is compounded (Mkik, M., Aya, M., Ghernouk, C., Boutaky, S., El Mousadik, M., & Hebaz, A. (2023, November).

That is where the theoretical benefits of AI come in, as AI can solve the problem. Machine-learning models have more information to work with than any analyst, and work the same way with each file, and are not fatigued, not sucked into mood, subjecting to the need to confirm a prior opinion. In the literature, many applications can be found such as the credit scoring systems (Bahrammirzaee, 2010), fraud detection (Leo et al., 2019), market risk and portfolio construction (Milana and Ashta, 2021). The question for bank management, however, is not WHETHER AI can perform more computations than can human beings, but rather WHETHER bank management decisions can be better made by using AI? If the algorithm is not applied or only applied if it corresponds to a prevailing belief, it could have no effect on the quality of the decision, or even be detrimental to it (Dietvorst et al., 2015).

Morocco is a pertinent context for this question. The banking sector is concentrated, well-capitalized, more and more digital, and technological innovation is one of the axes of the capital-market regulator's strategic plan, in addition to a dedicated artificial intelligence roadmap, which is being prepared (AMMC, 2025; AMMC, 2026). At the same time, there is descriptive empirical finance literature on AI in Morocco and the mechanisms through which the adoption of AI affects decision outcomes in banking firms are very limited (Marouane, M., Mkik, S., & El Menzhi, K. (2021).

This study is one that fulfills this void. It questions whether AI and financial decision making performance correlate in the Moroccan banking industry and how this correlation is manifested in three specific ways: risk management reinforcement, rationalization of decision making and control of behavioural biases. There are three aspects to the contribution. The first is that the research proposes a parallel mediation model instead of combining the three types of mediation together as AI. Secondly, it calculates the relative weight of each channel using bootstrap contrasts. Third, it offers empirical data from a North African banking sector which rarely has been studied in the literature.

The novelty of this paper lies in three aspects: First, most studies on the use of AI in finance focus on the accuracy of the algorithm (credit scoring, fraud detection, forecasting), whereas this paper focuses on the human decision maker, and on how the use of AI changes the way a banking decision maker makes that decision, linking two literatures that have developed separately – behavioral finance and AI adoption. Second, in our knowledge to date, it is the first study that tests all three channels (the psychological channel (bias control), the technical channel (risk management) and the procedural channel (decision rationality) in one parallel mediation model, and that ranks the three channels statistically, which means that one can draw the conclusion that through which channel, through which mechanism, AI rationalizes financial decisions, and not just proclaims that it does. Third, it provides original evidence from Morocco, an emerging banking market in North Africa, hosting conventional and participative banking and where the governance of AI has not yet been codified, to contribute to the early AI governance practices. After this, the rest of the paper follows this structure. The goals of this literature review in section 2 are building of research hypotheses, focusing on bounded rationality, behavioral biases, risk management and AI adoption. The methodology, such as sampling procedure, measurement instrument and analytical strategy are presented in Section 3. The results of the measurement model, the regression analyses and the mediation tests are reported in Section 4. Findings and managerial and regulatory implications of the study is discussed in section 5 along with limitations of the study. Section 6 concludes.

2. Literature Review and Hypotheses

a. Artificial intelligence, bounded rationality and bias control

Behavioral biases are the result of the use of heuristics to reduce the amount of effort placed on thinking about a decision (Tversky and Kahneman, 1974; Kahneman, 2011). Individuals often look for and remember information that validates their prior views or expectations, undervalue the adjustment from a basic value, and overvalue the accuracy of their own information (Nickerson, 1998; Odean, 1998). In addition to bias, professional judgments exhibit unwanted variability (noise) among professionals making the same decisions when faced with a similar problem, Kahneman et al. (2021) add. An algorithm by its nature, cannot introduce noise: the output of an algorithm is the same for any given input. They can also include evidence that opposes the first argument, and establish a standard for making a judgment. What was once an issue of "algorithm aversion" people are more likely to follow algorithmic recommendations seriously, Logg et al. (2019) show. Therefore, AI use should help decision makers to curb their bias.

H1. AI adoption is positively associated with the control of behavioral biases in financial decisions.

b. Artificial intelligence and risk management

AI is most commonly applied in banks for risk management. The use of machine-learning techniques has also increased to better recognise changes in credit quality early in the life of a loan, enhance the accuracy of credit risk prediction and manage the exposure to the market and identify fraudulent transactions (Aziz and Dowling, 2019; Leo et al., 2019). These can be used to process high frequency, unstructured data, and thus provide the possibility of real-time monitoring of exposure rather than at a scheduled reporting date. But the benefits are contingent on the quality of data and the models as elements of risk management (Ashta and Herrmann, 2021).

H2. AI adoption is positively associated with risk management capability.

c. Artificial intelligence and decision rationality

Procedural rationality is a rationality that stems from producing a decision, rather than from the rationality of the decision (Simon, 1955). A rational process is a process that is based upon objective data, compares the alternatives systematically, follows consistent criteria, and can be justified by measurable indicators. All of these features have been made possible by AI tools: structuring the information set, creating similar scores for other solutions, and providing a trace of the criteria they applied. Therefore, the adoption of AI should rationalise the decision-making process itself.

H3. AI adoption is positively associated with decision rationality.

d. Decision-making performance and mediating mechanisms

The Technology Acceptance Model (TAM; Davis, 1989) and its extended version (Venkatesh et al., 2003) imply that perceived usefulness of a technology has an impact on the performance of technology supported tasks, suggesting that the more useful a technology is perceived to be, the better the tasks can be performed. Performance in financial decision making is the quality, timeliness, reliability and effectiveness of the activity of financial decision making and the satisfaction of the persons who make decisions to it. The idea is that, instead of just giving users access to the algorithm, they can use its products to make decisions, as AI is made its way into financial services, Belanche et al. (2019) and Hama, A., Mkik, M., Khaddouj, K., & Hebaz, A. (2024, April)..

H4. AI adoption is positively associated with decision-making performance.

For AI to do a better job of performance, there need to be mechanisms that are clear that will show how it does. A better decision maker would be one who has more control of his biases, a better risk measure and a more rational way of decision making; if other things remain equal, the deciding person should have made a better decision. It is therefore logical that the three constructs of H1 to H3 could account for the performance and even some of the effect of adopting the use of AI.

H5a, H5b, H5c. Bias control, risk management and decision rationality are each positively associated with decision-making performance.

H6. These three mechanisms mediate the relationship between AI adoption and decision-making performance.

3. Methodology

a. Sample and data collection

This is derived from a questionnaire survey carried out in the banking and financial sector in Morocco with 200 professionals from the industry. The respondents work in financial decision-making positions – e.g. risk managers, client advisers, financial analysts, finance executives, internal auditors and managers. A non-probability purposive sampling method along with Snowball sampling technique was used since there was no sampling frame available for banking professionals in the public domain that could be used for sampling. The target population are financial professionals at Moroccan banks and financial institutions (commercial banks, participative banks, investment banks, asset management companies), who are responsible for financial decision making. The inclusion criteria were: (i) working in one of these institutions in Morocco; (ii) working in an office where he or she had direct involvement in financial decisions (credit, investment, risk assessment, control or management); and (iii) having an office position of at least one year. The participants were recruited both through professional networks (the members and direct contacts within the institution were contacted) and by the initial participants (s Snowball sampling) who forwarded the questionnaire to others with a similar profile. The activity of the Moroccan banking sector, which is highly centralized with Casablanca-Settat and Rabat-Salé-Kénitra being the main agglomerations has been taken into consideration during the collection of quotas by type of institution and by region. The questionnaire was mailed by e-mail from [month year] to [month year]. A total of [N] professionals were e-mailed with a questionnaire, a response rate of [x]% (200 questionnaires were returned, [x] were incomplete or inconsistent). Participants were not required and anonymous, and were told that the study was for academic purposes. The results are not necessarily representative of all Moroccan banking professionals because it is not a probability sample and can only be generalized with caution, particularly for the financial centre of the Kingdom, Casablanca-Settat.

A summary of the profile of the respondents is presented in Table 1.

Table 1: Profile of respondents (N = 200)

Variable	Category	%
Gender	Male / Female	61.0 / 39.0
Age (years)	Mean 35.2; SD 8.7; range 23–58	–
Experience (years)	Mean 8.2; SD 5.6; range 1–24	–
Education	Master (Bac+5)	63.5
	Bachelor (Bac+3)	18.0
	Doctorate	11.5
	Other higher education	7.0
Institution	Commercial bank	73.5
	Participative bank	10.0
	Asset management / UCITS	8.5
	Investment bank	8.0
Position	Risk manager	20.0
	Client adviser	19.5
	Financial analyst	18.0
	Finance executive	16.0
	Internal auditor / control	13.5
	Manager	13.0
Region	Casablanca-Settat	38.5
	Rabat-Salé-Kénitra	23.5
	Tanger-Tétouan-Al Hoceïma	13.5
	Fès-Meknès	11.0
	Marrakech-Safi	7.5
	Other regions	6.0

b. Measurement instrument

The questionnaire is bilingual (French and English) and has 5 constructs with a 5-point Likert scale ranging from 1 strongly disagree to 5 strongly agree. AI adoption (AIA, five items) refers to the adoption and usage of AI tools in the institution, integration of AI tools into decision making processes, personal use, consideration of AI recommendations and investment in AI skills. Bias control (BBR; 4 items): perceived capacity of AI to help avoid overconfidence, confirmation bias and anchoring, and to affect the capacity to make a fair evaluation of alternatives. Risk management (RM, 4 items) refers to recognizing risks at an early stage, the quality of the risk assessment, monitoring and anticipating adverse events as they happen. Decision rationality (DR, four items) is the use of objective information, a systematic comparison of alternatives, consistency in process and justification by measurable indicators. The dependent variable: Decision Making performance (DMP, five items) reflects decision quality, speed, outcomes, reliability in complex situations and satisfaction with decision processes. Construct scores are the average of the items.

c. Analytical strategy

The analysis is in three stages. The first one is a test of the measurement model via Cronbach's alpha, as well as the composite reliability (CR), average variance extracted (AVE) and the heterotrait-monotrait ratio (HTMT) by Henseler et al. (2015). The second (OLS) estimate the effect of AI adoption on each mechanism (equation 1) and the combined effect of the adoption of AI and the mechanisms on performance (equation 2):

$$M = a_0 + a \cdot AIA + \Sigma\gamma C + \varepsilon \quad (1)$$

$$DMP = b_0 + c'AIA + b_1 \ BBR + b_2 \ RM + b_3 \ DR + \Sigma\delta C + \varepsilon \quad (2)$$

where M is the group of BBR, RM and DR and C is the controls or the control variables, gender, professional experience, institution type (commercial bank versus other) and education level (Master or Doctorate versus other). Since age was highly correlated with experience ($r = 0.909$), age was not included. The third step is the estimation of the indirect effects with 5,000 percentile bootstrap resamples (Preacher and Hayes, 2008) in a parallel mediation model (Zhao et al., 2010). The robustness checks reported are for heteroscedasticity-consistent standard errors (HC3), variance inflation factors and residual tests. Estimations were made in Python (Statsmodels).

4. Results

a. Reliability and validity of the measurement model

Table 2 shows the results of all constructs have acceptable reliability criteria (Nunnally, 1978; Hair et al., 2019). This convergent validity is achieved because the Cronbach's alpha falls between 0.825 and 0.935, the composite reliability is within the range of 0.884 to 0.951 and all the AVE is above the threshold of 0.50. Items have construct loadings that range from 0.772 to 0.906. Factorability of the data is indicated by the Kaiser-Meyer-Olkin index which is 0.932 and the highly significant Bartlett's test of sphericity ($\chi^2 = 2{,}913.3$; $df = 231$; $p < 0.001$).

Table 2: Reliability, convergent validity and descriptive statistics

Construct	k	α	CR	AVE	Mean	SD
AI adoption (AIA)	5	0.863	0.902	0.648	3.582	0.789
Bias control (BBR)	4	0.825	0.884	0.656	3.417	0.779
Risk management (RM)	4	0.872	0.913	0.724	3.564	0.871
Decision rationality (DR)	4	0.899	0.930	0.768	3.459	0.946
Performance (DMP)	5	0.935	0.951	0.794	3.526	1.038

The scores of all constructs are above the scale midpoint of 3, ranging from 3.417 for bias control to 3.582 for AI adoption. The respondents' least confidence is in AI reducing their cognitive biases (3.417), compared with AI improving risk management (3.564) or decision performance (3.526). Skewness and kurtosis for each of the constructs are within ±1.

There is some evidence for discriminant validity (Table 3). The square root of each AVE is greater than the construct's correlations with each other construct. The HTMT ratios of all of them are lower than the conservative ratio of 0.85, the highest being the ratio of decision rationality/performance of 0.803.

Table 3: Correlations, √AVE (diagonal) and HTMT (above diagonal)

	AIA	BBR	RM	DR	DMP
AIA	0.805	0.391	0.625	0.641	0.701
BBR	0.329	0.810	0.234	0.408	0.464
RM	0.543	0.199	0.851	0.560	0.655
DR	0.564	0.351	0.497	0.876	0.803
DMP	0.630	0.407	0.593	0.736	0.891

Note. Below the diagonal: Pearson correlations, all significant at $p < 0.01$. Diagonal: square root of AVE (Fornell and Larcker, 1981). Above the diagonal: HTMT ratios.

Common method variance was checked using Harman's single factor variance (Podsakoff et al., 2003) since all the variables were obtained from the same respondents. Four factors have eigenvalues >1 with the first unrotated factor accounting for 44.8% of the total variance which is below the 50% criterion. Thus, common method variance is not likely to be responsible for the results, but it may be.

b. Effect of AI adoption on the three mechanisms

The estimates of equation (1) are given in Table 4. The results support the hypothesis H1, H2 and H3 as all the mechanisms are positively and significantly related to the adoption of AI. There are positive significant correlation for Rationality of decisions ($\beta = 0.558$), risk management ($\beta = 0.544$) and weaker bias control ($\beta = 0.307$). About one third of the variance in decision rationality and in risk management could be explained by AI adoption, and 13.4% of variance in bias control could be explained by AI adoption. All of the control variables are insignificant at the 5% level.

Table 4: Effect of AI adoption on the mediating mechanisms

Dependent	B	β	t	R^2	F(5,194)
Bias control	0.303	0.307	4.53***	0.134	6.00***
Risk management	0.601	0.544	9.00***	0.309	17.38***
Decision rationality	0.669	0.558	9.36***	0.330	19.10***

*Note. Coefficients of AIA; models include gender, experience, institution type and education. *** $p < 0.001$.*

c. Determinants of decision-making performance

The estimates of equation (2) are shown in Table 5. The model explains 67.3% of the variance in decision-making performance (adjusted $R^2 = 0.659$; $F(8,191) = 49.03$; $p < 0.001$). The most important variables are decision rationality ($\beta = 0.452$), Risk management ($\beta = 0.220$), AI adoption ($\beta = 0.219$) and Bias control ($\beta = 0.132$). All four are significant to support H4, H5a, H5b and H5c.

Table 5: Determinants of decision-making performance

Predictor	B	β	t	p	95% CI
Constant	–0.943	–	–3.08	0.002	[–1.546; –0.340]
AI adoption	0.288	0.219	3.97	<0.001	[0.145; 0.432]
Bias control	0.175	0.132	2.90	0.004	[0.056; 0.295]
Risk management	0.262	0.220	4.24	<0.001	[0.140; 0.384]
Decision rationality	0.496	0.452	8.43	<0.001	[0.380; 0.613]
Gender (male)	0.155	0.073	1.73	0.085	[–0.021; 0.331]
Experience	–0.012	–0.065	–1.53	0.127	[–0.028; 0.003]
Commercial bank	0.093	0.040	0.94	0.347	[–0.102; 0.287]
Higher education	0.164	0.069	1.60	0.110	[–0.038; 0.365]

Note. $N = 200$; $R^2 = 0.673$; adjusted $R^2 = 0.659$; residual SE = 0.606; $F(8,191) = 49.03$, $p < 0.001$.

Table 6 shows the hierarchy of the explanatory power. The variance is only explained by 4.3 % of socio-demographic controls. The three mechanisms have an additional positive effect of 24.1 points on R^2, while adding AI adoption has an additional positive effect of 38.8 points on R^2. Both these are significant hikes.

Table 6: Hierarchical regression of decision-making performance

Step	R^2	Adj. R^2	ΔR^2	F change
1. Controls	0.043	0.024	–	–
2. + AI adoption	0.431	0.417	0.388	132.32***
3. + Mechanisms	0.673	0.659	0.241	46.92***

*Note. F change df = (1,194) at step 2 and (3,191) at step 3. ***$p < 0.001$.*

d. Mediation analysis

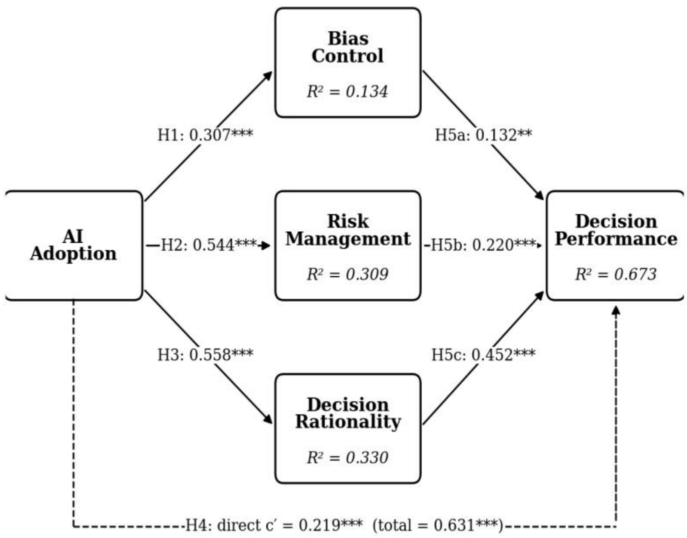
The total effect of the use of AI on performance ($c = 0.831$; $\beta = 0.631$; $p < 0.001$) is reduced to $c' = 0.288$ (direct effect), when adding the three mechanisms. Table 7 shows the estimates of the indirect effects, which were calculated by bootstrap. All three are significant since none of their respective 95% confidence intervals contains 0, thus supporting H6. The mechanisms act together to pass through 0.542 units of the effect, or 65.3% of the total effect. The mediation is partial and complementary in the sense of Zhao *et al.* (2010) as the direct effect is still significant with the same sign as the indirect effects.

Table 7: Bootstrap estimates of indirect effects (5,000 resamples)

Path	Effect	SE	95% CI
AIA → BBR → DMP	0.053	0.023	[0.013; 0.103]
AIA → RM → DMP	0.157	0.045	[0.079; 0.249]
AIA → DR → DMP	0.332	0.049	[0.238; 0.432]
Total indirect	0.542	0.069	[0.414; 0.679]
Direct effect (c′)	0.288	0.073	[0.145; 0.432]
Contrast DR – BBR	0.279	0.056	[0.171; 0.390]
Contrast DR – RM	0.175	0.069	[0.040; 0.303]
Contrast RM – BBR	0.104	0.047	[0.019; 0.200]

The pairwise contrasts provide a definite ranking of the channels. The indirect effect, through decision rationality, is significantly larger than the indirect effect, through risk management, and the indirect effect, through risk management is significantly larger than the indirect effect, through bias control. The total indirect effect is shared between decision rationality (61%), risk management (29%) and bias control (10%). Standardized path-coefficients are summarized in figure 1.

Figure 1: Research model with standardized coefficients



$**p < 0.01$; $***p < 0.001$.

e. Robustness checks

Estimates are robust. Multicollinearity is not an issue for the full model as the variance inflation factors are acceptable (1.03 - 1.77). The Breusch-Pagan test does not reject the null hypothesis of homoscedasticity at 5% level ($p = 0.077$), and the standard errors computed on HC3 are the same for each conclusion. The Durbin-Watson statistic is of 2.068, the residuals are normally distributed (Jarque-Bera $p = 0.874$; Shapiro-Wilk $p = 0.995$) and the maximum Cook's distance is 0.046. This pattern is supported by a median split on the level of AI use: decision-making performance is significantly higher for high users (4.061 vs. 2.898; $t = 9.41$; $p < 0.001$; $d = 1.12$), risk management is significantly higher for high users (3.975 vs. 3.082; $t = 8.32$; $p < 0.001$; $d = 1.03$), decision rationality is significantly higher for high users (3.838

vs. 3.014; $t = 6.78$; $p < 0.001$; $d = 0.87$), and bias control is slightly higher for high users (3.618 vs. 3.182; $t = 4.11$; $p < 0.001$; $d = 0.56$). By contrast, AI adoption does not differ significantly across institution types ($F(3,196) = 0.95$; $p = 0.417$), nor does performance across positions ($F(5,194) = 1.41$; $p = 0.220$).

Table 8: Summary of hypothesis tests

Hypothesis	Relationship	Result
H1	AIA → Bias control	Supported
H2	AIA → Risk management	Supported
H3	AIA → Decision rationality	Supported
H4	AIA → Performance	Supported
H5a	Bias control → Performance	Supported
H5b	Risk management → Performance	Supported
H5c	Decision rationality → Performance	Supported
H6	Mediation by the three mechanisms	Partial

5. Discussion

The results are consistent with the hypothesis of using AI as a tool for rationalizing financial decision making in Moroccan banks. The most informative finding though is the way this rationalization operates: AI does not mainly correct the psychology of the decision maker. The two most important advantages of AI's ability to make better decisions is its ability to restructure the way decisions are made, and its ability to measure the risk more effectively.

The most important channel is decision rationality. It is the strongest determinant of performance and its indirect effect is 6 times as great as that of bias control. This is in keeping with Simon's (1955) distinction between substantive and procedural rationality: AI is not replacing the banker, but it is giving him a procedure, based on objective data, systematic comparison, consistent criteria and measurable justification – one which limits the space in which he uses his human judgment. The model is akin to Kahneman et al. (2021) which is about disciplining the decision process, rather than about fixing the person.

Not surprisingly, the second channel is risk management, as risk management is the first and most intensive user of machine learning in banking (Aziz and Dowling, 2019; Leo et al., 2019). Moreover, the adoption of AI is highly positively associated with risk management ($\beta = 0.544$) indicating that Moroccan professionals believe that there are clear advantages in being alert to risks in the early stages, getting it right, and monitoring exposures in real-time.

The weakest connection is the control of bias and that is what qualifies the first premise. It has the lowest variance explained by the use of AI (13.4%), the lowest mean of all constructs and the lowest indirect effect, at just 10% of the total indirect effect. There are two possibilities for the interpretation. The first one is that there's some confirmation bias which has to be removed, and there's no tool to remove it, because if the algorithm recommends something, the user will do it if they think so, and they won't do it if they don't think so. The second is bias control is less noticeable compared to risk or process improvement because people don't typically know about their biases. In either scenario, it is not sufficient for banks to simply implement a plan for adopting AI to offset behavioral bias.

Lastly, after controlling for these three channels, the significant direct impact of AI adoption suggests other channels not represented in the model, such as potential time savings, or information richness or the legitimacy that comes with decisions based on algorithms. It's a partial instead of a full mediation.

a. Managerial and regulatory implications

The results suggest that the profitability of AI investments for bank managers depends on the use of AI in the decision-making process, rather than on the availability of AI tools. The most powerful channel found in this study is the use of AI-generated recommendations in credit committees, investment decisions and risk assessment, and the guidelines on how to document, implement and challenge the recommendations. Explicit debiasing practices, such as making sure that the algorithmic recommendation is justified when it is not followed, giving disconfirming evidence where possible, and training individuals in behavioral finance, should be implemented when using AI. Results indicate a need for a governance framework for the application of AI in decision-making, both in the supervisory context and in the roadmap (which will be prepared by the capital-market authority (AMMC, 2025)) context.

b. Limitations and future research

It should be noted that there are a number of caveats. It is a cross-sectional design, which means that the relationships are associations; not causal. All constructs are self-reported and Harman's single common factor test does not reveal a dominant common factor, and variance might be contaminated by common method variance. Most importantly, the wording of the mediators and outcome items is in the participant's own perspective, e.g., the perceived impact of AI is to reduce anchoring, to improve the quality of decisions. They capture the perception that AI has been helpful, but not the amount of bias or the impact of decisions measured independently. Future studies could combine survey findings with traditional, objective metrics such as loan default rates, or experimental metrics of biases, using longitudinal designs to follow an institution before and after AI was implemented. Additionally, further testing of the results with structural equation modeling and multi-group analysis of the results based on the type of institution would be beneficial, especially for participative banks. Finally, the data is limited to only a small number of non-probability sampling methods (purposive, snowball sampling) and a probability sample would be preferable to generate a more representative sample, thus improving the external validity of the findings.

6. Conclusion

The study reveals that the use of AI has a statistically significant relationship with the performance of decision making in the banking sector in Morocco, with about two thirds (65.3%) of this relationship transmitted through three pathways. AI rationalizes financial decisions in three ways: Firstly, by structuring the process of the decision-making itself; secondly, by improving risk management; and, only marginally, by decreasing behavioral biases – all of which contribute to rationalization. The lesson to be learned from the hands-on experience is that AI can be used for procedural rationality, not cognitive bias. AI isn't simply a matter of technology, it's an investment in AI decision governance and behavioral awareness that Moroccan banks must make in order to truly power up with AI.

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