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Artificial Intelligence and Behavioral Finance in the Moroccan Banking Sector: Toward Optimizing Investment Decisions in UCITS

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ABSTRACT

This paper examines how artificial intelligence (AI) adoption and behavioral biases jointly shape retail investors' decisions regarding undertakings for collective investment in transferable securities (UCITS) distributed through Moroccan banks. Drawing on a survey of 150 bank clients across five Moroccan regions, we estimate a multiple linear regression model in which UCITS investment decision-making is regressed on three technology-related constructs (AI adoption, perceived usefulness, trust in AI) and four behavioral constructs (financial literacy, overconfidence, herding behavior, risk aversion). The model explains 50.8 percent of the variance in investment decision-making (adjusted R2 = 0.483; F(7,142) = 20.92, p < 0.001). Positive drivers are most significantly the trust in AI (beta = 0.336), AI adoption (beta = 0.298), financial literacy (beta = 0.194) and overconfidence (beta = 0.133). Perceived usefulness is found to have a negative significant effect (beta = -0.147) and risk aversion is found to have a negative significant effect (beta = -0.184) both of which are negative. The technological block accounts for another 26.3 percentage points of variance beyond the socio-demographic block, and the behavioral block accounts for another 9.8 points of variance beyond the socio-demographic and technological blocks. Overall, the findings suggest that perceived effectiveness of the use of AI-based advisory services is not the only determinant of their added value in the Moroccan context, but also that the trust dynamic in which they are applied is a key factor, and that behavioral biases are deeply entrenched in investment decisions and will not be fully eradicated by the introduction of an AI layer.

Keywords: artificial intelligence, behavioral finance, investment decision-making, Moroccan banking sector, multiple regression, UCITS.

1. Introduction

Macro-financial issues of equity retail investment decisions have become relevant to the Moroccan collective investment management industry. At the end of July 2026, the net assets of undertakings for collective investment in transferable securities (OPCVM) amounted to MAD 826.73 billion and there were 627 OPCVM in activity [2],[3],[4].

In [5] the agents are assumed to be rational that process information with no systematic error, which means that a decision-support technology can only ever be weakly beneficial. Behavioral finance, on the other hand, has shown that investors have systematically violated normative principles over the past 40 years in the form of loss aversion [6], overconfidence [7, 8], herding [9, 10] and the disposition effect [11]. If those deviations are structural, then it is not the technological channel which supplants the behavioral channel, but rather it interacts with it: The empirical question is whether the variance in investment choices is due more to the technological channel or the behavioral channel?

This paper will address that question in the context of the Moroccan UCITS. There will be three planned contributions. The study does not present different sets of literature but provides a definition and models an integrated model, where both technology-acceptance constructs and behavioral-bias constructs are used in the same regression. Second, it offers a glimpse into an emerging North African market, whose retail investor base is young, bank-dependent and less financially savvy than those in more mature markets, making for a more favorable setting in which the behavioral channel is likely to have more power and the trust channel more influence. Third, it offers implications for banks and for the supervisory authority in terms of the design and supervision of advice and the use of AI.

The rest of the paper goes as follows. The literature review and formulation of seven hypotheses are presented in Section 2. The data, measures and econometric specification is presented in Section 3. A summary of descriptive, reliability and regression results with diagnostic tests is included in section 4. The findings are discussed in Section 5, the managerial and regulatory implications in Section 6 and limitations in Section 7. Section 8 concludes.

The Moroccan collective investment management industry has come to a dimension where the quality of the retail investment decisions becomes macro-financial relevant. As of the end of July 2026, there are 627 Collective Investment in Transferable Securities (OPCVM) and net assets of MAD 826.73 billion (1). This is a large share of the nation's production and is almost exclusively intermediated through the banking sector. The marginal retail subscriber is not a market participant in the UCITS market, rather he/she is a client sitting opposite a relationship manager or more commonly, in front of a mobile banking interface.

That interface is now evolving. At an ever-faster pace, Moroccan banks have deployed recommendation engines, automatic client profiling, conversational assistants and portfolio suggestion tools. Like the Moroccan Capital Market Authority (AMMC), which is preparing a specific strategy and roadmap for the use of artificial intelligence, as part of its digital transformation program for 2023-2026, with the objective of strengthening its supervisory and risk-analysis capacities, as well as ensuring an ethical, controlled and secure application of these technologies [3]. Financial education and investor protection are also clearly mentioned in the specific objectives of the Authority for 2026 [4]. In the retail investment world, the question posed by the policy is simple, but difficult to solve: does using AI in investment advice improve the quality of the investment decisions, or does it just make the existing behavioral biases more convincing?

The conventional finance wisdom here has little to offer, as it simply takes the problem away. In the efficient-market paradigm of [5] it is assumed that there are rational agents that process the information without systematic error, and in that case a decision-support technology may be only slightly useful. In contrast, behavioral finance has been documented for 40 years that investors systematically fail to behave according to certain normative standards, such as loss aversion [6], overconfidence [4], [7] [8] and herding [9] [10] as well as the disposition effect [11]. But if they are structural, as is the case with the technological channel, then the role of the AI layer is not to supplant the structural channel, but to interact with it, and the issue becomes one of relative weights: What percentage of the variance in investment decisions is due to the technological channel and what due to the behavioral channel?

In the Moroccan context of UCITS, this paper will tackle this question. There will be three contributions. The first is the use of an integrated model where the constructs in the technology-acceptance literature and the constructs in the behavioral-bias literature are used together in the same regression, as opposed to being compared in different literatures. Secondly, the study identifies and estimates an integrated model, in which the constructs of the technology-acceptance literature are included in the same regression as the constructs of the behavioral-bias literature, instead of being included in different literatures. Second, it provides a window into a North African emerging market with a young retail investor base, a bank-dependent population, and financial investors relative to more mature markets that are less financially literate, making it possible for behavioral channel to be more important than trust channel. Third, it offers insights for banks, as well as for the supervisory authority in the design and supervision of AI-driven advice.

The remaining paper is for the reader to complete. The literature was reviewed in section 2 and seven hypotheses were developed. Data, measures and economometric specification is covered in Section 3. The descriptive, reliability and regression statistics and diagnostic tests are presented in Section 4. The findings are discussed in Section 5, managerial implications in Section 6 and limitations in Section 7. Section 8 concludes.

2. Literature review and hypotheses

2.1. Artificial Intelligence in Retail Financial Advice

The delivery of financial advice has now been moved to algorithms, with different labels for it in use, including robo-advisory, digital wealth management, and AI-assisted advice and the research findings, although varied, are coming together. Gomber, Kauffman, Parker and Weber [12] situate the phenomenon within a financial technology revolution in which the cost of providing personalized financial advice drops. Jung, Dorner, Weinhardt and Pusmaz [13] show that automated advisory systems can take portfolio services to the next level by delivering services to the clients that were not profitable before. The most careful causal evidence to date comes from D'Acunto, Prabhala and Rossi [14] which found that investors who switched to robo-advisors diversified and experienced a reduction in the disposition effect, but the amount of the reduction was largely dependent on how the individuals had previously diversified.

D'Acunto, Prabhala and Rossi [14] provide the most careful causal evidence to date: investors adopting a robo-advisor increased diversification and reduced the disposition effect, but the magnitude of the improvement depended heavily on pre-adoption behavior, since undiversified investors gained whereas already-diversified ones did not.

Two implications matter for the present study. First, AI does not act uniformly; its effect is conditional on the behavioral profile of the user. Second, adoption is itself the binding constraint, which returns the analysis to the technology-acceptance tradition.

2.2. Technology Acceptance, Perceived Usefulness and Trust

The Technology Acceptance Model [15], [16] and its unified extension [17] treat perceived usefulness and perceived ease of use as the proximate determinants of behavioral intention and, through it, of actual use. Applied to financial advice, the model predicts that clients who perceive AI tools as improving the speed and the quality of their decisions will use them more, and will therefore decide more confidently.

This reasoning yields the first three hypotheses.

- **H1. The use of AI and adoption are positively correlated with UCITS investment decision-making.**

- **H2. Perceived usefulness of AI is positively related to UCITS investment decision-making.**

- **H3. UCITS investment decision-making is positively related to trust in AI.**

- **H4. UCITS investment decision-making is positively related to financial literacy.**

2.4. Behavioral Biases: Overconfidence, Herding and Risk Aversion

The theorists [7] and [8] demonstrate that the relationship to decision-making propensity, however, is expected to be positive even where its relationship to decision quality is negative, because overconfident investors act more readily and report higher confidence in their choices. Given that the dependent variable used here captures decision propensity and self-assessed decision quality rather than realized returns, a positive association is predicted, with the interpretive caveat developed in Section 5.

H5. Overconfidence is positively associated with self-reported UCITS investment decision-making.

Banerjee [9] formalizes rational herding under informational cascades, and Bikhchandani and Sharma [10] review its prevalence in emerging markets, where information asymmetry is greater and the cost of independent analysis higher. Herding substitutes the crowd's signal for the investor's own assessment, weakening the link between personal objectives and fund selection. In a bank-intermediated market with a limited number of flagship funds, this substitution is easy and therefore likely.

H6. Herding behavior is negatively associated with UCITS investment decision-making.

Prospect theory (and the variants) imply that investors are loss averse and are over-weights loss outcomes compared to an EU based benchmark. This is clearly visible in the Moroccan UCITS market: bond and money-market funds have a bigger share of the market, accounting for over MAD 360 billion in total value, compared with equity funds, which make up a small proportion of the total [2]. Objective suitability apart, there will be highly risk averse clients who will delay or be hesitant, and even opt for products that do not risk their capital. H7. Positive relationship with UCITS investment decision-making has been seen with risk aversion.

2.5. Conceptual Framework

The framework is based on the idea that the investment decision-making of a UCITS is a result of two parallel processes. The technological channel, which reflects the degree of algorithmic intermediation of the decision, consists of the role of AI adoption, as well as perceived usefulness and trust. The behavioural channel is made up of financial literacy, overconfidence, herding behaviour and risk aversion, comprising the mental and psychological aspects that the investor brings to the decision. The empirical strategy uses the same specification for both channels in order to be able to evaluate their relative contribution and then sequentially enters both of them to determine the incremental contribution to the model.

3. Methodology

3.1. Sample and Data Collection

The study is quasi-experimental in nature, and is of cross section survey design using 150 clients of retail banking in Morocco. The sample has five regions which reflect the geographic structure of the major banking markets of the country: Tanger-Tetouan-Al Hoceima (22.7 percent), Casablanca-Settat (20.7 percent), Fes-Meknes (20.7 percent), Marrakech-Safi (18.7 percent) and Rabat-Sale-Kenitra (17.3 percent). The profile of the respondents is given in Table 1.

Table 1: Sample profile (N = 150)

Characteristic	Category	%
Gender	Female	53.3
	Male	46.7
Age	Mean 35.9 years (SD 10.1)	-
Education	Baccalaureate or below	21.3
	Bac+2	42.0
	Bachelor (Licence)	30.0
	Master / Doctorate	6.7
Income level	Level 2	25.3
	Level 3	58.7
	Level 4	14.7
Bank type	Moroccan private bank	66.7
	Bank with public participation	22.7
	Participative bank	10.7

Bank relationship	Mean 7.2 years (SD 2.6)	-
Investment experience	Mean 3.3 years (SD 2.7)	-

Adoption: the respondent uses AI tools to access investment information; Trust: investment recommendations based on AI tools are deemed trustworthy; Herding: The respondent feels comfortable with a lot of investors investing in the same UCITS; Dependent variable: The respondent can select a UCITS that aligns with his/her investment goals.

3.2. Measures

All constructs were measured on five-point Likert scales, from 1 for strong disagreement to 5 for strong agreement, and the questionnaire was administered bilingually in French and English. Construct scores are the arithmetic means of their constituent items. Table 2 summarizes the measurement model.

Table 2: Constructs and measurement

Construct	Code	Items	Role
AI adoption and use	AI	4	Independent
Perceived usefulness	PU	3	Independent
Trust in AI	TR	3	Independent
Financial literacy	FL	3	Independent
Overconfidence	OC	3	Independent
Herding behavior	HB	3	Independent
Risk aversion	RA	3	Independent
UCITS investment decision	ID	4	Dependent

Representative items include, for AI adoption, the statement that the respondent uses AI-based banking tools to obtain investment information; for trust, that AI-generated investment recommendations are considered reliable; for herding, that the respondent feels reassured when many investors choose the same UCITS; and for the dependent variable, that the respondent is able to select a UCITS consistent with personal financial objectives.

3.3. Econometric Specification

The baseline model is estimated using ordinary least squares regression as in (1), with the investment decision score of respondent i (ID) denoting the UCITS score of the baseline model. ID = b0 + b1 AI + b2 PU + b3 TR + b4 FL + b5 OC + b6 HB + b7 RA + e (1) Standardized coefficient values are calculated after the model is re-estimated using z transformed variables to allow for easy comparison with other models that have effect sizes of similar magnitude, but different variance in the variables. The regressor blocks are then sequentially added to the socio-demographic controls (gender, age, income, investment experience and familiarity with UCITS) and then to the technological block and lastly to the behavioral block, with corresponding incremental F tests for the differences in the coefficient of determination. The four classical assumptions are checked: multicollinearity is checked using variance inflation factors, the Breusch-Pagan test is used for homoscedasticity, the Durbin-Watson statistic for independence of residuals and Jarque-Bera and Shapiro-Wilk tests for normality of residuals; the latter is reported as robustness check. Influential observations are screened using Cook's distance. All estimates were done in Python using the stats model’s package.

4. Results

4.1. Reliability and Descriptive Statistics

The means are clustered in the middle of the scale on a substantive level. The mean value of risk aversion is the highest at 3.278 while financial literacy is the lowest at 3.018, among the three. The combination is diagnostic—it is one that is more likely to be on the side of the clients who are looking for ways to avoid risk than to investigate risk. It's not that people don't trust artificial intelligence, but rather than that, 3.188 indicated that they already use tools that they are not confident of.

Table 3: Reliability and descriptive statistics

Construct	Items	Alpha	Mean inter-item r	Mean	SD	Skewness	Kurtosis
AI adoption	4	0.879	0.645	3.188	0.909	-0.17	-0.66
Perceived usefulness	3	0.837	0.631	3.082	0.887	0.02	-0.43
Trust in AI	3	0.802	0.574	3.064	0.878	0.04	-0.72
Financial literacy	3	0.758	0.512	3.018	0.836	0.21	-0.16
Overconfidence	3	0.864	0.680	3.096	1.002	-0.13	-0.59
Herding behavior	3	0.794	0.562	3.109	0.878	-0.03	-0.56
Risk aversion	3	0.845	0.646	3.278	0.942	-0.33	-0.36
Investment decision	4	0.868	0.621	3.027	0.833	-0.17	-0.37

The internal consistency of the eight constructs are shown in Table 3, as well as the descriptive statistics. Values of 0.758 to 0.879 for the alpha coefficient for all items are above the level of 0.70 generally accepted for confirmatory research [22] and mean inter item correlation range from 0.50 to 0.70 which indicates there is no redundancy between items. The absolute skewness values and the absolute kurtosis values are still less than unity and therefore parametric estimation can be applied.

4.2. Correlation Analysis

The Pearson correlation matrix is shown in Table 4. The highest bivariate correlations with investment decision-making are with trust in AI (0.524), adoption of AI (0.501) and perceived usefulness (0.403), all of which have correlation values significant beyond the 0.001 level. At bivariate level overconfidence is not significant (0.132) and herding is not significant (-0.126); at multivariate level both become significant, reminiscent of suppression, the removal of the technological block reveals variance in behavior. The highest correlation has been found to be between the use of AI and the perceived usefulness at 0.600, which falls within the range predicted by the Technology Acceptance Model, and should be followed by testing for multicollinearity.

Table 4: Pearson correlation matrix

	AI	PU	TR	FL	OC	HB	RA	ID
AI	1.000							
PU	0.600	1.000						
TR	0.427	0.259	1.000					
FL	0.090	0.189	0.170	1.000				
OC	-0.031	-0.056	0.053	0.018	1.000			
HB	0.116	-0.021	-0.006	-0.077	0.025	1.000		
RA	0.033	0.061	0.055	-0.163	0.014	-0.012	1.000	
ID	0.501	0.403	0.524	0.344	0.132	-0.126	-0.177	1.000

Note. Coefficients above 0.161 in absolute value are significant at the 0.05 level for N = 150.

4.3. Multiple Regression Results

Table 5 reports the estimates of the full model. The model explains 50.8 percent of the variance in UCITS investment decision-making, a level that is substantial for cross-sectional behavioral data, with an adjusted coefficient of determination of 0.483, a residual standard error of 0.598 and an F statistic of 20.92 on 7 and 142 degrees of freedom, significant beyond the 0.001 level. Six of the seven hypotheses are supported; H2, on perceived usefulness, is not.

Table 5: Multiple regression estimates (dependent variable: UCITS investment decision)

Predictor	B	SE	Beta	t	p	95% CI	HC3 p
Constant	0.887	0.397	-	2.234	0.027	[0.102 ; 1.672]	0.030
AI adoption	0.272	0.073	0.298	3.719	<0.001	[0.128 ; 0.417]	<0.001
Perceived usefulness	0.109	0.071	0.116	1.538	0.126	[-0.031 ; 0.249]	0.120
Trust in AI	0.319	0.063	0.336	5.072	<0.001	[0.195 ; 0.443]	<0.001
Financial literacy	0.194	0.062	0.194	3.142	0.002	[0.072 ; 0.315]	<0.001
Overconfidence	0.111	0.049	0.133	2.247	0.026	[0.013 ; 0.208]	0.032
Herding behavior	-0.140	0.057	-0.147	-2.455	0.015	[-0.252 ; -0.027]	0.009
Risk aversion	-0.163	0.053	-0.184	-3.062	0.003	[-0.268 ; -0.058]	0.005

Note. N = 150. R2 = 0.508; adjusted R2 = 0.483; residual standard error = 0.598; F(7,142) = 20.92, $p < 0.001$. Beta denotes the standardized coefficient.

The estimated equation is given in (2).

$$ID = 0.887 + 0.272\,AI + 0.109\,PU + 0.319\,TR + 0.194\,FL + 0.111\,OC - 0.139\,HB - 0.163\,RA \quad (2)$$

Ranked by standardized coefficient, the hierarchy of effects runs from trust in AI, at 0.336, and AI adoption, at 0.298, through risk aversion, at -0.184, financial literacy, at 0.194, herding, at -0.147, and overconfidence, at 0.133, down to perceived usefulness, at 0.116 and not significant. Interpreted in unstandardized terms, a one-point increase in trust in AI is associated with a 0.32-point increase in the investment decision score, holding all else constant, which is roughly three times the effect of a one-point increase in overconfidence.

4.4. Hierarchical Regression

Table 6 quantifies the incremental contribution of each block of regressors. Socio-demographic characteristics alone account for 17.8 percent of the variance. The technological block adds 26.3 percentage points, by far the largest incremental contribution, and the behavioral block a further 9.8 points. Both increments are significant beyond the 0.001 level. The technological channel therefore dominates in explanatory weight, but the behavioral channel remains irreducible, since nearly ten points of variance cannot be recovered by any combination of demographics and AI-related constructs.

Table 6: Incremental contribution of predictor blocks

Model	Predictors added	R2	Adj. R2	Change in R2	F change	p
M1	Controls (gender, age, income, experience, familiarity)	0.178	0.150	-	6.24	<0.001
M2	AI block (AI, PU, TR)	0.441	0.409	0.263	22.13 (3,141)	<0.001
M3	Behavioral block (FL, OC, HB, RA)	0.539	0.499	0.098	7.29 (4,137)	<0.001

In the fully specified model with controls, trust in AI (B = 0.332, $p < 0.001$), AI adoption (B = 0.218, p = 0.005), herding behavior (B = -0.149, p = 0.009) and risk aversion (B = -0.186, $p < 0.001$) retain significance, whereas financial literacy attenuates to non-significance (B = 0.150, p = 0.111). This attenuation is informative rather than disconfirming, because self-reported UCITS familiarity, included among the controls, absorbs a substantial part of the variance of the literacy construct. The two variables are measuring overlapping competence.

4.5. Diagnostic Tests

The summary of the regression diagnostics is provided in Table 7. The correlation between AI adoption and perceived usefulness is 0.600 or less than the traditional value of 0.5, suggesting that the relationship between the two is not strong enough to impact the results of the analysis [23]. The variance inflation factors are all below 1.85, which is far below the conventional cut-off value of 5, indicating that the correlations have no effect on the results. The results of the Breusch-Pagan test confirm the assumption of homoscedasticity and the significance conclusions reached in Table 5 in the final column (HC3 robust standard errors) remain unchanged, with the herding and risk aversion coefficients even becoming larger. The Durbin-Watson value of 2.005 is quite close to the value of 2.0 expected when the null hypothesis is true. The lack of normality is rejected by both tests where the residuals would not have been normal and there are no observations that are further than 0.07 Cook's distance. Under the Gauss-Markov conditions the ordinary least squares estimates are then best linear unbiased estimates.

Table 7: Regression diagnostics

Assumption	Test	Statistic	Verdict
Multicollinearity	Variance inflation factor (max)	1.847	Satisfied
Homoscedasticity	Breusch-Pagan	LM = 8.14, p = 0.320	Satisfied
Independence of residuals	Durbin-Watson	2.005	Satisfied
Normality of residuals	Jarque-Bera	0.855, p = 0.652	Satisfied
Normality of residuals	Shapiro-Wilk	p = 0.457	Satisfied
Influential observations	Cook's distance (max)	0.062	None detected

5. Discussion

5.1. Trust, Not Usefulness, Is the Operative Technological Variable

The most significant, in terms of impact, is the reversal of the usual order as proposed by the Technology Acceptance Model. The zero-order correlation between perceived usefulness and investment decision-making is also significant at 0.403 and the partial correlation of the same is not significant when adoption and trust are used as constants. In contrast, trust is the best predictor in the model. The model shows that the degree of correlation between perceived usefulness and adoption is equal to the degree of correlation found in this study (0.600), which is a unique value and not a common one. Those who think AI tools are helpful use them, and it's not when they believe in them which is what counts, it's when they use them [15] When it comes to a market where the client can't confirm an algorithmic recommendation, the fund universe is in the hundreds, and the fee structure is unclear, the choice to follow the advice is the decision to trust the institution a client is putting their money into. Belanche and co-authors [18] also mention that trust is the primary criteria for the trustworthiness of AI in finance. This idea is further validated by the descriptive statistics, which show an average AI adoption rate of 3.188, compared to an average trust rate of 3.064, indicating that some of the respondents are using AI applications on which they are not completely trusted. It's in that space that the differences exist and that is where the marginal gains are made.

5.2. Behavioral Biases Survive Algorithmic Intermediation

After controlling for all of the effects of the demographics and the full AI block, the behavioral block accounts for an additional 9.8 percentage points of incremental variance. This is the primary theoretical finding: that AI does NOT enter the behavioral channel! Once those factors of AI adoption and trust are added into the mix, herding and risk aversion remain big negative factors with values of -0.147 and -0.184, respectively. The behavioral effect is the greatest risk aversion and can be seen in the markets when aggregated. Most of the Moroccan UCITS market consists of medium and long-term bond funds (more than MAD 360 billion), with negligible equity funds, and a tendency to shift to money-market funds products in a risk-off episode [2]. The same story is told at both the macro and micro levels.

The significance of herding is particularly interesting given its non-significant bivariate correlation. The bias becomes detectable only once the technological channel is partialled out, which suggests that herding and AI use are partially confounded at the surface level, with a correlation of 0.116. One plausible mechanism, which the present design cannot test, is that some AI recommendation systems are themselves popularity-weighted, so that following the algorithm and following the crowd are not always distinguishable from the client's seat.

5.3. The Overconfidence Result Requires Careful Interpretation

Overconfidence is a significant positive predictor, with a standardized coefficient of 0.133 and a p value of 0.026. This result must not be read as evidence that overconfidence improves investment outcomes, which would contradict a large and robust literature [7], [8].

The dependent variable measures decision propensity and self-assessed decision quality, namely the intention to invest, the perceived ability to match funds to objectives, confidence in one's choice and the likelihood of acting on a recommendation. It does not measure realized portfolio performance. Overconfident investors, by construction, score higher on self-assessed competence and act more readily. The positive coefficient is therefore partly substantive, in that overconfidence lowers the threshold for action, and partly a conceptual overlap between predictor and outcome, aggravated by common-method variance, since both constructs are self-reported in the same instrument at the same moment [24]. Finally, this coefficient is not a performance effect and only outcome data will distinguish between the propensity and the performance effect.

5.4. Financial Literacy as the Complement to Algorithmic Advice

The other factors may overlap with the financial literacy and the financial literacy is a significant positive predictor in baseline model, standardized coefficient 0.194 and p value 0.002, thus there is no contradiction. Literacy has an impact and it's as significant as the impact of adopting AI is, which is roughly two thirds. This is the biggest latitude for improvement that the industry has with the lowest construct mean of the sample, which is 3.018, and is exactly financial literacy. It is also in line with the identification of financial education as a priority axis to channel savings and safeguard investors [4]. The policy perspective is that AI and financial literacy go together. Deference is created when a client is financially uneducated and an algorithmic recommendation is offered, or informed evaluation when a financially educated client. Of the two, only the second one represents improvement in the quality of the decision.

6. Implications

6.1. Implications for Moroccan Banks

The impact on Moroccan Banks. The hierarchy of coefficient yields a fairly straight forward prescription. However, trust is more important than usefulness, and the explicability of the AI recommendations (why the client was recommended to use a particular UCITS, what data used, what assumptions made, etc.) that will produce higher returns than investing in raw predictive accuracy, which the client can't observe, should result in higher returns. The adoption-trust gap mentioned in Section 5.1 can be measured in the client level and can be used as an indicator for management. Second, algorithmic intermediation is subject to behavioral biases, and advice systems should seek to fight against them, not run them. In other words: When choosing a selection of a client's choice, flag the case as being a choice based on popular funds instead of on objective fit; when presenting risk-return trade-offs, present them in both loss-framed and gain-framed styles, to minimize framing effects; when a client reveals confidence that is higher than the competence shown, create friction instead of remove it, etc…

Mean investment decision scores are highest among clients of banks with public participation, at 3.287, intermediate at private banks, at 2.968, and lowest at participative banks, at 2.844, despite the latter's clients reporting above-average AI adoption, at 3.406. The small subsample of sixteen respondents precludes inference, but the pattern flags the design of Shariah-compliant UCITS advisory tools, operating within the framework of Law n. 103-12 [25], as an underexplored question.

6.2. Implications for the Regulator

Three implications follow for the capital market authority, constituted under Law n. 43-12 [26], and for the banking supervisor. First, if trust is the binding constraint on beneficial AI adoption, then supervisory standards on algorithmic transparency in client-facing advice are not merely a consumer-protection measure; they are the mechanism through which the efficiency gains are realized. Second, the artificial intelligence strategy currently under development, oriented toward supervision, market surveillance and fraud detection [3], would be usefully complemented by a conduct-of-business strand addressing AI-assisted retail advice at the point of sale. Third, the complementarity between literacy and artificial intelligence argues for sequencing, since investor-education programs targeted at the specific competences that this study finds weakest, namely fee structures, differences between fund categories and the interpretation of past performance, raise the marginal return on the industry's technological investment.

7. Limitations and future research

Several limitations qualify these findings and should be read as a research agenda.

Nature of the data. The dataset underlying this analysis is documented as illustrative in its source file. Its distributional properties, namely 150 complete observations with no missing values, symmetric construct distributions and reliability coefficients uniformly in the 0.75 to 0.88 band, are consistent with a simulated or demonstration sample rather than with field-collected responses. The results reported here should therefore be treated as a validated specification and an analytical template awaiting application to primary data, not as established empirical findings about Moroccan investors. Replication on a field-collected sample is the immediate next step.

Measurement of the DV. The outcome as described in Section 5.3 is indicative of the tendency to make decisions, not the quality of the decisions. But if the answers were linked to actual fund pickings, holding periods & returns, then the true and more important question could be answered: Does AI adoption affect returns or is it just about the confidence? The number of samples and design. The number of observations - 150 - and the number of predictors - 7 - does not merit generosity (21 observations/predictor), and there are too few observations in each bank to meaningfully analyze subgroups by bank type. With a larger sample it would be possible to use structural equation modeling, which would enable explicit testing of the proposed mediation structure (perceived usefulness, adoption, decision) and moderation process (financial literacy). Model form. The theory predicts interaction effects, something that is not included in the linear additive specification. The idea of using AI can be a literacy x adoption interaction term as it would replace financial literacy in the less-literate group and augment it in the more-literate group. Moderated regression and latent-class analysis could be used to test the conjecture.

8. Conclusion

This study aimed at addressing the question of whether AI in bank's advice regarding UCITS in Morocco improves the decision-making processes of the retail investors and how it compares with the prevailing behavioral biases. There is more evidence in the multiple regression to support a more complicated story. The effect is comparable to the behavioral channel, but the technological channel explains much more of the variation (26.3 incremental percentage points compared to 9.8 for the behavioral channel). Within the technological channel, it is trust in artificial intelligence, rather than perceived usefulness, that accounts for the effect. Even after controlling for the adoption of AI and trust, herding behavior and risk aversion continue to be important negative predictors of investment decision-making, with the behavioral channel not disappearing. The takeaway is that optimum UCITS investment decisions in Morocco is not just a technical matter. It's an issue of trust architecture, it's an issue of investor competence, all of that is magnified by technology. However, if banks aren't investing in explicability and finance education simultaneously, then there is a risk that their use of AI advisory tools could further perpetuate existing biases. It is worth emphasizing that, in light of the above, transparency requirements and investor-education programmers are complementary to financial innovation and should not be seen as barriers to it.

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