Data Governance and Ai Governance: Effects on Value Creation in Moroccan Financial Organizations the Mediating Role of Trust in AI and the Influence of Behavioral Biases (Algorithm Aversion and Algorithm Overconfidence)

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Abstract:

This research examines the effect of data governance and artificial intelligence governance on value creation in Moroccan financial organizations. The proposed model integrates two central explanatory mechanisms - trust in AI and decision quality - as well as two behavioral biases that may influence the appropriation of algorithmic systems, namely algorithm aversion and overconfidence. Based on a cross-sectional survey administered to 134 professionals working in banks, insurance companies, asset management firms, and fintechs, the study assesses the reliability and validity of the constructs, diagnoses common method bias, and then tests the hypotheses using robust regressions and bootstrap mediation. The results indicate that data governance and AI governance strengthen trust in AI, that trust improves decision quality, and that decision quality constitutes the most important proximal determinant of value creation. Data governance also retains a significant direct effect on value, whereas AI governance acts mainly indirectly through trust and decision quality. From a managerial perspective, the study highlights that the sustainable value of AI does not depend solely on the technical performance of models, but on their organizational framing, their auditability, and the ability of actors to develop calibrated trust.

Keywords: *AI governance, behavioral biases, data governance, decision quality, Moroccan financial sector, trust in AI, value creation.*

1. Introduction

Over the last decade, financial organizations have experienced a profound transformation in their management practices, customer relationships, and risk management under the combined effect of digitalization, the explosion of data volumes, and the diffusion of artificial intelligence tools. In banks, insurance companies, asset management firms, and fintechs, algorithms are used for scoring, fraud detection, segmentation, offer optimization, control automation, portfolio management, and compliance support. However, the value promise of AI remains unevenly realized. Many organizations invest in advanced analytical solutions without managing to transform these technical capabilities into sustainable organizational performance. This situation shifts attention away from the mere power of tools toward the organizational conditions that make their appropriation, legitimacy, and economic impact possible.

One of the major lessons of recent research is that AI does not create value by itself. Its contribution depends on data quality, the robustness of control procedures, the clarity of responsibilities, model transparency, the management of algorithmic risk, and the ability of users to make appropriate use of the recommendations provided to them. This is why the issue of governance now occupies a central place in both scientific and professional debates. On the one hand, data governance aims to guarantee the availability, quality, traceability, security, and compliance of the data feeding the models. On the other hand, AI governance seeks to frame the life cycle of systems, from design to post-deployment monitoring, in order to limit bias, manage incidents, maintain performance, and make decisions auditable.

In financial organizations, these issues are particularly acute. The sector handles sensitive data, operates in a regulated environment, and makes decisions that may have considerable legal, economic, and reputational consequences. An algorithmic system that lacks transparency, is insufficiently monitored, or is fed by poor-quality data may not only harm performance, but may also undermine the trust of employees, clients, and supervisory authorities. Conversely, a strong governance framework can reduce uncertainty, clarify controls, secure uses, and encourage a more confident and more effective use of AI in decision-making processes.

At the same time, the literature on trust in AI shows that adoption does not rely solely on technical performance criteria. Trust constitutes a fundamental cognitive and organizational mechanism that enables users to rely on complex systems when making decisions. However, this trust can be poorly calibrated. Excessive distrust may lead to the underuse of otherwise high-performing systems, whereas blind trust may result in forms of over-delegation, automation bias, or algorithmic followership. Value creation therefore depends not only on the presence of governance mechanisms, but also on the way these mechanisms shape trust and orient decision quality.

In the Moroccan context, these questions remain only weakly explored empirically, even though the financial sector is experiencing an acceleration in digitalization projects, data exploitation, and analytical automation.

Available studies focus more on technology adoption, digital service quality, or perceptions of innovation, and less on the articulation between data governance, AI governance, trust, behavioral biases, and value creation. This gap justifies the present study, which seeks to propose an integrative framework capable of explaining how the organizational framing of data and algorithms can translate into value in Moroccan financial organizations.

The general research question may therefore be formulated as follows: to what extent do data governance and AI governance influence value creation in Moroccan financial organizations, and through which mechanisms - in particular trust in AI and decision quality - do these effects unfold, in the presence of behavioral biases such as algorithm aversion and overconfidence?

From this question, the study pursues three complementary objectives. The first is to establish whether governance arrangements actually strengthen trust in AI. The second is to verify whether this trust translates into better decision quality. The third is to determine whether decision quality indeed constitutes the main channel through which governance produces value.

At the theoretical level, the research contributes to the literature by articulating three perspectives that are often treated separately: the governance of informational resources, trust in AI systems, and behavioral biases in algorithm-assisted decisions. At the empirical level, it tests the model using a survey conducted in the Moroccan financial sector. At the managerial level, it highlights the importance of concrete stewardship, documentation, monitoring, human control, and organizational learning mechanisms in transforming the promises of AI into effective performance.

2. Literature Review

2.1. Data governance and value creation

Data governance refers to the set of structures, rules, and processes that organize the production, sharing, security, and use of data within the firm. It typically includes the clarification of roles and responsibilities, quality policies, coding standards, data dictionaries, cataloging, transformation traceability, access control, and compliance mechanisms. In the recent literature, data governance is increasingly considered a cross-functional organizational capability, that is, a set of routines and mechanisms that make it possible to transform data into an exploitable strategic asset. Bernardo et al. (2024) show that data governance and data quality management constitute a major lever for innovation and performance across a range of sectors, notably because of their effect on analytical reliability, cross-functional coordination, and error reduction.

In the financial sector, this dimension is even more critical. Data condition risk assessment, product personalization, customer relationship management, and regulatory compliance. Data that are inconsistent, incomplete, or poorly traced can weaken the entire analytical chain, up to destroying the relevance of technically sophisticated models. Thus, the value derived from data depends not only on their volume or accessibility, but on their governance. Research on digital transformation also stresses that technological investments have an impact only when they are supported by governance structures capable of aligning the production and use of data with the strategic objectives of the organization.

A growing part of the literature also points out that data governance is no longer limited to technical dimensions. It includes issues of informational sovereignty, security, ethics, accountability, and value sharing among actors. In data-intensive environments, firms must define who can access which information, according to which rules, for what purpose, and under which form of control. This orientation brings data governance closer to the notion of organizational trust: the more information flows are traced, qualified, and framed, the more users can rely on them to make decisions with confidence.

2.2. AI governance: principles, mechanisms, and organizational scope

Whereas data governance frames the informational raw material, AI governance aims to frame the life cycle of algorithmic systems. It refers to the set of principles, structures, and processes that make it possible to design, deploy, monitor, and adjust AI systems in a responsible, robust, transparent, and compliant manner. Institutional frameworks such as the NIST AI RMF (2023), ISO/IEC 42001 (2023), the OECD principles, and the European AI Act converge on several dimensions: risk management, documentation, human oversight, robustness, security, traceability, fairness, and accountability. These dimensions do not belong solely to technical engineering; they require explicit organizational governance, supported by roles, committees, review procedures, incident logs, and control protocols.

Papagiannidis et al. (2025) and Batool et al. (2025) show in their reviews that the main contemporary challenge no longer lies in formulating general principles, but in operationalizing them concretely. An AI system may be presented as ethical or trustworthy in institutional discourse while remaining poorly documented, insufficiently monitored, or weakly contestable in practice. AI governance therefore becomes the space in which the credibility of systems is actually played out. It is what links normative requirements to observable managerial actions: model validation before production, drift monitoring, control of training data, impact analyses, incident escalation processes, and the maintenance of human intervention when required.

In financial organizations, AI governance has a particular strategic value. It helps limit algorithmic risk, reduce decision opacity, and increase the acceptability of analytical tools. A scoring or recommendation system will not be sustainably adopted if it is perceived as an uncontrollable black box. By contrast, the more an organization is able to document, monitor, and explain its systems, the more it makes informed trust and the integration of AI into decision routines possible.

2.3. Trust in AI and decision quality

Trust in AI can be defined as the disposition of an individual or a collective to rely on the recommendations or outputs of an algorithmic system on the assumption that they are sufficiently competent, reliable, and aligned with the objectives of action. Glikson and Woolley (2020) show that this trust is built at the intersection of technical, relational, and contextual factors. Users consider the perceived performance of the system, its consistency, readability, level of autonomy, and the organizational signals that frame its use. Afroogh et al. (2024) also emphasize that trust is supported by axiological dimensions such as transparency, ethics, and the perception of fairness.

In an organizational context, trust in AI does not simply constitute a favorable attitude. It acts as a mechanism that conditions the way algorithmic recommendations are integrated into real decisions. Trust that is too low may lead actors to ignore a potentially useful aid; trust that is too high may lead them to follow recommendations without sufficient verification. The notion of calibrated trust therefore becomes essential. Recent literature on decision-support systems indicates that the value of AI depends on users' ability to adjust their reliance according to context, decision criticality, and signals of performance or doubt.

From this perspective, decision quality appears as the proximal link between trust and value. A high-quality decision is not merely a fast one; it is a more coherent, better justified, more relevant, and more organizationally aligned decision. When trust in AI is sufficiently high and properly calibrated, it can improve decision quality by reducing processing time, enriching analysis, and stabilizing trade-offs. When it is poorly calibrated, however, it may lead both to rejection errors and followership errors.

2.4. Behavioral biases: algorithm aversion and overconfidence

Behavioral research has identified two major biases in interactions with algorithmic systems. The first is algorithm aversion. Dietvorst, Simmons, and Massey (2015) show that individuals may turn away from an algorithm after observing an error, even when that algorithm remains statistically more accurate than human judgment. This phenomenon reflects a particular intolerance toward machine error and a stronger need for control or personalization when facing a tool perceived as cold, rigid, or opaque. In organizations, aversion may translate into low use of recommendations, a preference for human judgment, or quiet workarounds around AI tools.

The second bias is overconfidence, or algorithm appreciation in certain contexts. Logg, Minson, and Moore (2019) showed that individuals may sometimes prefer algorithmic judgment to human judgment, especially when the algorithm is perceived as more objective or more analytical. This tendency may nevertheless result in forms of automation bias: users follow a recommendation without examining it critically, or assign the machine an excessive expert status. Vasconcelos et al. (2023) show that meaningful explanations can help reduce this over-delegation, but only if they are embedded in a sufficiently reflective usage relationship.

In the financial sector, these two biases are strategically important. Aversion may reduce the return on AI investments by limiting their effective use. Overconfidence may, by contrast, generate short-term gains in fluidity while increasing the risks of erroneous decision, discrimination, or legal exposure. This justifies the explicit integration of these variables into the research model.

2.5. Toward an integrative model of value creation

Research on value creation from AI increasingly converges toward a socio-technical view. AI does not generate value only because it improves predictions or automates tasks; it creates value when it is supported by high-quality data, governance routines, accountability mechanisms, and appropriate organizational uses. In this logic, data governance and AI governance can be considered structural antecedents of trust, whereas decision quality represents the operational mechanism through which this trust is transformed into value.

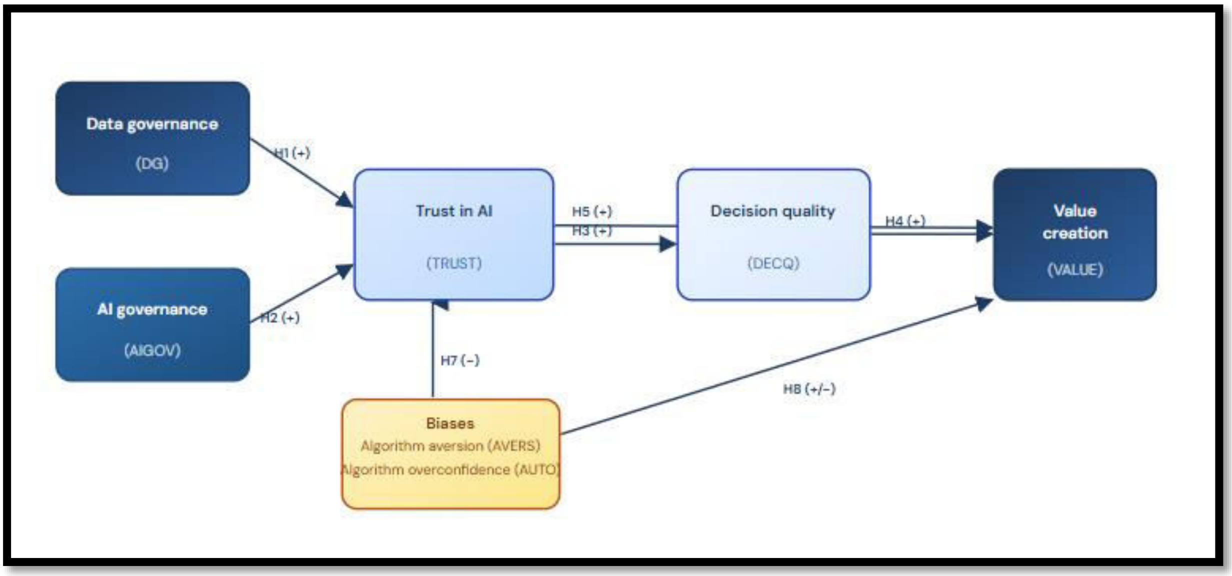
The model retained in this study is based on this articulation. It assumes that data governance and AI governance strengthen trust in AI. This trust positively influences decision quality, which in turn increases value creation. Algorithm aversion is expected to weaken the process, whereas algorithm overconfidence may have an ambivalent effect: it may be associated with greater perceived value, but at the cost of a risk of excessive dependence. This framework makes it possible to integrate simultaneously the institutional, cognitive, and behavioral dimensions of the relationship between AI and performance.

3. Presentation of the Conceptual Model

The conceptual model retained in this study seeks to explain value creation through a short but integrative theoretical causal chain. It starts from the idea that governance acts as an infrastructure of trust. Data governance ensures the reliability of informational inputs, whereas AI governance frames the algorithmic systems themselves through documentation, control, monitoring, and human oversight. Together, these two forms of governance reduce perceived uncertainty and strengthen trust in AI. This trust, when sufficiently calibrated, encourages the relevant use of algorithmic recommendations and translates into better decision quality. Value creation is therefore not conceived as an automatic effect of technologies, but as the outcome of a sequence linking governance, trust, decision, and performance. Behavioral biases are integrated as variables likely to influence the links in the model: algorithm aversion may hinder appropriation, whereas overconfidence may accelerate use but also increase the risks of over-delegation.

On this basis, eight hypotheses are formulated: H1, data governance is positively associated with trust in AI; H2, AI governance is positively associated with trust in AI; H3, trust in AI is positively associated with decision quality; H4, decision quality is positively associated with value creation; H5, data governance is positively associated with value creation; H6, the effect of AI governance on value creation is mainly indirect through trust and decision quality; H7, algorithm aversion is negatively associated with trust and value; H8, algorithm overconfidence is associated with value in an ambivalent way.

Figure 1. Research conceptual model



Source: Developed by the author.

4. Methodology

From an epistemological point of view, this research adopts an adapted positivist stance aimed at empirically testing an explanatory conceptual framework based on theorized relationships between latent variables. The design retained is quantitative, cross-sectional, and hypothetico-deductive. Data were collected through an online questionnaire administered to professionals from the Moroccan financial sector working in banks, insurance companies, asset management firms, and fintechs. The final sample comprises 134 usable responses. The constructs were measured on 7-point Likert scales. Data governance was captured through items relating to quality, standardization, traceability, security, and clarity of responsibilities. AI governance was measured through items dealing with documentation, monitoring, risk management, controls, and accountability. Trust in AI refers to perceived reliability and the propensity to rely on the system's recommendations. Decision quality reflects the perception of more coherent, more relevant, and more effective decisions. Value creation measures perceived benefits in terms of efficiency, risk reduction, performance improvement, and service quality. Two behavioral biases were integrated: algorithm aversion and algorithm overconfidence. The data were processed in Python. The analysis first focused on measurement quality, through Cronbach's alpha, composite reliability, Average Variance Extracted, the Fornell-Larcker criterion, and the HTMT index. A common method bias diagnosis was then conducted using Harman's one-factor test and Kock's full collinearity procedure. Finally, the hypotheses were tested by means of robust linear regressions with HC3 errors, including control variables related to tenure, type of organization, job function, firm size, and AI use intensity. Mediation effects were examined through bootstrap with 2,000 resamples. This methodological setup makes it possible to assess rigorously the associations between governance, trust, decision quality, and value creation while taking into account potential biases linked to the cross-sectional design.

5. Results

The sample is composed of 134 respondents and shows an average tenure of 12.96 years (SD = 7.26). The tables below present the descriptive profile, the quality of the measurement model, the structural relationships, and the mediation effects.

Table 1. Distribution of respondents by type of organization

	n	%
Bank	61.0	45.5
Insurance	34.0	25.4
Asset management company/AM	20.0	14.9
Fintech	11.0	8.2
Other	8.0	6.0

Source: Author's calculations based on survey data (N = 134).

In Table 1, we observe that the banking sector is the most represented group, followed by insurance, which is consistent with the structure of the Moroccan financial sector. The presence of asset management firms and fintechs broadens the spectrum of organizations covered by the study. This diversity strengthens the relevance of the model beyond a single type of institution. It also suggests that the findings are not limited to traditional banking alone. The distribution provides a credible basis for examining governance and AI-related practices in the financial field. Overall, the sample captures a meaningful cross-section of the sector.

Table 2. Distribution of respondents by job function

	n	%
Risk	30.0	22.4
Data/IT	28.0	20.9
Sales/Marketing	27.0	20.1
Executive management	18.0	13.4
Other	16.0	11.9
Conformité	15.0	11.2

Source: Author's calculations based on survey data (N = 134).

In Table 2, we observe that risk, data/IT, and sales/marketing functions are strongly represented, which is coherent with the themes of AI use, decision support, and value creation. The presence of executive management and compliance/audit functions also enriches the analysis. It indicates that the questionnaire reached respondents who are exposed to both operational and governance-related issues. Such a composition is useful because governance effects often cut across several departments. The sample therefore reflects organizational roles that are directly involved in the implementation and oversight of AI. This improves the substantive relevance of the empirical results.

Table 3. Distribution by organizational size

	n	%
>2000	48.0	35.8
500–2000	38.0	28.4
100–500	33.0	24.6
<100	15.0	11.2

Source: Author's calculations based on survey data (N = 134).

In Table 3, we observe that large organizations account for the largest share of the sample, but medium-sized and smaller entities are also represented. This is important because organizational size may influence governance maturity, analytical capabilities, and available resources. The coexistence of several size categories introduces meaningful heterogeneity into the data. It also justifies the inclusion of control variables in the regressions. The presence of smaller firms, including fintechs, prevents the study from being restricted to large incumbents only. Methodologically, this diversity supports a broader interpretation of the findings.

Table 4. Intensity of AI use in respondent organizations

	n	%
Moderate	45.0	33.6
High	38.0	28.4
Low	36.0	26.9
Very high	15.0	11.2

Source: Author's calculations based on survey data (N = 134).

In Table 4, we observe that the intensity of AI use is distributed across low, moderate, and high levels, with no single category monopolizing the sample. This distribution is useful because it provides variation in how respondents experience AI systems in practice. Such variation increases the explanatory power of the model. It also indicates that the study captures organizations at different stages of AI maturity. The coexistence of moderate and high-intensity users is particularly informative for a governance-related analysis. The variable is therefore methodologically relevant as both a contextual and a control factor.

Table 5. Descriptive statistics, reliability, and convergent validity of the constructs

	k	Alpha	CR	AVE	M	SD
DG	5.000	0.831	0.881	0.597	3.981	1.151
AIGOV	5.000	0.859	0.899	0.639	3.991	1.185
AVERS	3.000	0.648	0.810	0.588	3.993	1.132
AUTO	3.000	0.739	0.852	0.657	3.975	1.216
TRUST	4.000	0.879	0.917	0.733	3.993	1.268
DECQ	4.000	0.842	0.894	0.679	3.972	1.247
VALUE	5.000	0.893	0.921	0.701	4.006	1.251

Source: Author's calculations based on survey data (N = 134).

Note. Alpha = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted.

In Table 5, we observe that Cronbach's alpha and composite reliability coefficients show a satisfactory level of internal consistency for most constructs. The AVE values exceed the thresholds commonly retained in the literature, which supports convergent validity. The constructs used in the study therefore appear sufficiently stable to be employed in structural analysis. Measurement quality is especially important in a model combining governance, trust, and behavioral biases. These results strengthen the empirical credibility of the research design. They allow the interpretation of relationships among variables to proceed with an adequate level of methodological confidence.

Table 6. Correlation matrix and Fornell-Larcker criterion

	DG	AIGOV	AVERS	AUTO	TRUST	DECQ	VALUE
DG	0.772	0.481	0.073	0.075	0.440	0.218	0.462
AIGOV	0.481	0.800	-0.184	-0.019	0.606	0.454	0.493
AVERS	0.073	-0.184	0.767	0.054	-0.194	-0.181	-0.199
AUTO	0.075	-0.019	0.054	0.811	-0.068	-0.086	0.118
TRUST	0.440	0.606	-0.194	-0.068	0.856	0.507	0.526
DECQ	0.218	0.454	-0.181	-0.086	0.507	0.824	0.615
VALUE	0.462	0.493	-0.199	0.118	0.526	0.615	0.837

Source: Author's calculations based on survey data (N = 134).

In Table 6, we observe that the Fornell-Larcker criterion is globally satisfied, since the square root of AVE remains higher than the corresponding correlations on the diagonal. This indicates that each construct shares more variance with its own indicators than with the other constructs in the model. The result supports discriminant validity. It is particularly important for empirically distinguishing data governance from AI governance. It also helps separate trust in AI from decision quality. Overall, the measurement model appears conceptually coherent**.**

Table 7. Discriminant validity according to the HTMT ratio

	DG	AIGOV	AVERS	AUTO	TRUST	DECQ	VALUE
DG	1.000	0.568	0.141	0.183	0.515	0.260	0.536
AIGOV	0.568	1.000	0.249	0.121	0.699	0.534	0.564
AVERS	0.141	0.249	1.000	0.087	0.256	0.243	0.262
AUTO	0.183	0.121	0.087	1.000	0.125	0.140	0.169
TRUST	0.515	0.699	0.256	0.125	1.000	0.589	0.595
DECQ	0.260	0.534	0.243	0.140	0.589	1.000	0.709
VALUE	0.536	0.564	0.262	0.169	0.595	0.709	1.000

Source: Author's calculations based on survey data (N = 134).

In Table 7, we observe that HTMT values remain below the critical thresholds usually retained in the literature, which further supports the discriminant validity of the measurement model. This result usefully complements the Fornell-Larcker criterion. It reduces the risk of excessive overlap between constructs. In particular, it reinforces the distinction between governance dimensions and the psychological mechanisms related to trust. Taken together, the diagnostics support the quality of the measurement model. This stage is essential before examining structural relationships.

The common method bias diagnosis indicates that the first unrotated factor explains 31.8% of the total variance, which is below the 50% threshold generally used. At the same time, the maximum full-collinearity VIF is 2.19, which is below the 3.3 threshold.

The two tests converge toward the idea that common method variance does not dominate the observed relationships. This is important in a study based on a self-administered questionnaire, where methodological bias can never be completely ruled out. The result strengthens the credibility of the empirical associations between governance, trust, decision quality, and value. It nevertheless does not authorize a strict causal interpretation, given the cross-sectional nature of the data. A cautious reading in terms of associations therefore remains necessary. The following analyses may be considered sufficiently robust for discussing the hypotheses of the model.

Table 8. Results of the model explaining trust in AI (R2 = 0.480)

	Standardized beta	SE	t	p	Sig
DG_z	0.233	0.087	2.667	0.008	**
AIGOV_z	0.453	0.095	4.783	0.000	***
AVERS_z	-0.108	0.080	-1.346	0.178	
AUTO_z	-0.084	0.076	-1.102	0.270	

Source: Author's calculations based on survey data (N = 134).

Note. Robust regressions with HC3 standard errors.

In Table 8, we observe that both data governance and AI governance exert a positive and significant effect on trust in AI, which validates hypotheses H1 and H2. The effect of AI governance appears stronger, suggesting that mechanisms dedicated to the algorithmic life cycle directly influence the perceived credibility of systems. Behavioral biases do not dominate this model once governance arrangements are taken into account. Trust therefore seems to be institutionalized by the organization. This result is consistent with the literature on trustworthy AI. It shows that trust is as much organizational as it is psychological.

Table 9. Results of the model explaining decision quality (R2 = 0.366)

	Standardized beta	SE	t	p	Sig
TRUST_z	0.378	0.110	3.433	0.001	***
DG_z	-0.055	0.098	-0.565	0.572	
AIGOV_z	0.269	0.120	2.238	0.025	*
AVERS_z	-0.102	0.091	-1.121	0.262	
AUTO_z	-0.033	0.084	-0.391	0.696	

Source: Author's calculations based on survey data (N = 134).

Note. Robust regressions with HC3 standard errors.

In Table 9, we observe that trust in AI positively and significantly influences decision quality, which validates H3. This result shows that algorithmic recommendations become useful when they are perceived as sufficiently reliable to be integrated into decision routines. AI governance also retains a direct effect, which suggests procedural benefits independent of trust. Decision quality thus appears as a central intermediate link. It translates the transformation of a climate of trust into decision performance. This result directly prepares the analysis of value creation.

Table 10. Results of the model explaining value creation (R2 = 0.586)

	Standardized beta	SE	t	p	Sig
DECQ_z	0.451	0.083	5.446	0.000	***
TRUST_z	0.158	0.089	1.772	0.076	dagger
DG_z	0.317	0.084	3.763	0.000	***

AIGOV_z	0.023	0.104	0.221	0.825	
AVERS_z	-0.100	0.076	-1.322	0.186	
AUTO_z	0.188	0.071	2.637	0.008	**
TRUSTxAVERS	-0.011	0.066	-0.167	0.867	
TRUSTxAUTO	-0.013	0.062	-0.215	0.830	

Source: Author's calculations based on survey data (N = 134).

Note. Robust regressions with HC3 standard errors.

In Table 10, we observe that decision quality constitutes the strongest determinant of value creation, which validates H4 and shows that decision performance is the most immediate mechanism of value production. Data governance retains a significant direct effect on value, which validates H5 and suggests benefits that go beyond AI uses alone. By contrast, the direct effect of AI governance is not significant once the mediators are integrated. This supports the idea of a mainly indirect effect. Overconfidence shows a positive but potentially ambivalent effect. Finally, the non-significant interactions suggest that biases play more of a direct role than a moderating one.

Table 11. Indirect mediation effects obtained through bootstrap (2,000 resamples)

	Estimate	Lower 95% CI	Upper 95% CI
DG -> TRUST -> DECQ -> VALUE	0.040	0.008	0.083
AIGOV -> TRUST -> DECQ -> VALUE	0.078	0.023	0.150
DG -> TRUST -> VALUE	0.037	-0.002	0.099
AIGOV -> TRUST -> VALUE	0.071	-0.007	0.153

Source: Author's calculations based on survey data (N = 134).

Note. An indirect effect is considered significant when the confidence interval does not include zero.

In Table 11, we observe that the sequential indirect effects DG -> TRUST -> DECQ -> VALUE and AIGOV -> TRUST -> DECQ -> VALUE are significant, since their confidence intervals do not include zero. This confirms that value creation passes through a structured mediating chain. Governance first improves trust, then trust improves decision quality, and it is decision quality that produces value. Simple mediations through TRUST alone also exist, but they are weaker. The central role of decision quality is therefore confirmed. The model gains both theoretical and empirical coherence.

5.1. Hypothesis validation

Table 12. Summary of hypothesis validation

	Tested link	Expected effect	Empirical result	Decision
H1	DG -> TRUST	Positive	Beta=0.233 ; p=0.008	Supported
H2	AIGOV -> TRUST	Positive	Beta=0.453 ; p<0.001	Supported
H3	TRUST -> DECQ	Positive	Beta=0.378 ; p=0.001	Supported
H4	DECQ -> VALUE	Positive	Beta=0.451 ; p<0.001	Supported
H5	DG -> VALUE	Positive	Beta=0.317 ; p<0.001	Supported
H6	AIGOV -> VALUE	Mainly indirect	Direct beta=0.023 ; p=0.825 ; indirect effects significant	Supported as indirect effect
H7	AVERS -> TRUST / VALUE	Negative	Non-significant in full models	Partially supported / not supported in full models
H8	AUTO -> VALUE	Ambivalent	Beta=0.188 ; p=0.010	Partially supported

Source: Author's calculations based on survey data (N = 134).

In Table 12, we observe that the synthesis of hypotheses shows strong support for most of the central relationships in the model. Hypotheses H1 to H5 are supported, which confirms the main sequence linking governance, trust, decision, and value. Hypothesis H6 is also supported insofar as the effect of AI governance on value appears mainly indirect. By contrast, the hypotheses related to behavioral biases are only partially confirmed. This reflects a more nuanced influence of aversion and overconfidence. Nevertheless, the overall assessment of the model remains robust.

6. Discussion

The results of this study show that value creation stemming from AI in Moroccan financial organizations cannot be understood without taking into account the governance mechanisms that frame both data and algorithms. The relationship between governance and performance appears indirect, structured by intermediate mechanisms of trust and decision quality. This reading fits within a socio-technical perspective according to which value is not produced by technology in itself, but by the organizational arrangements that make its use reliable, legitimate, and useful. Recent frameworks on trustworthy AI emphasize precisely this articulation between technical robustness, oversight, transparency, and accountability. The empirical results obtained here move in the same direction by showing that governance produces value only when it is translated into the mindsets and practices of users.

A first major lesson concerns the distinction between data governance and AI governance. Both dimensions positively influence trust in AI, but their role is not identical when it comes to explaining value. Data governance retains a significant direct effect on value creation. This result is consistent with the reviews by Bernardo et al. (2024), which show that governance and data quality directly improve analytical performance, coordination, and error reduction. In the financial sector, this direct effect may be explained by the fact that better qualified and better traced data strengthen management control, reporting quality, compliance, and the reliability of analyses, even outside strictly algorithmic uses. Data governance therefore acts as a broader infrastructure of value than AI itself.

By contrast, AI governance does not exert a significant direct effect on value once trust and decision quality are introduced. This is an important theoretical result. It suggests that AI governance is not, by itself, a source of immediately perceptible performance; rather, it acts as a device of credibility and appropriation. The reviews by Papagiannidis et al. (2025) and Batool et al. (2025) converge on this point: the central challenge of responsible governance is not merely to proclaim principles, but to make systems observable, contestable, and steerable. In our study, AI governance creates value because it nourishes trust and supports better decision quality. Its impact is therefore mainly processual and mediating, rather than direct and autonomous.

A second central result concerns precisely the role of trust in AI. The work of Glikson and Woolley (2020), as well as Afroogh et al. (2024), shows that trust is built on signals of competence, reliability, transparency, and fairness. Our results extend this literature by showing that trust can be institutionalized through governance. Users do not trust AI only because they perceive it as performant; they trust it more when they operate in an environment where roles, rules, controls, and system monitoring are clear. This dimension is especially important in regulated sectors, where trust cannot rely solely on intuition or habituation of use. It must be supported by visible and legitimizing arrangements.

However, trust does not appear as an end in itself. The model shows that the most decisive variable for explaining value creation is decision quality. This point is essential. It means that trust becomes productive only when it is transformed into more relevant, more coherent, and more effective decisions. This conclusion echoes the criticisms directed at some technology-adoption research that too quickly assimilates intention or trust with performance. Between trust and performance, there exists an organizational space where the quality of trade-offs, the integration of recommendations, and the ability to combine human judgment with algorithmic outputs are played out. Our results show that this conversion space is fundamental: trust acts mainly through decision quality, which reinforces the relevance of a sequential mediation scheme.

Behavioral biases add a more nuanced layer of interpretation. Contrary to what the literature on algorithm aversion might lead one to expect, aversion does not emerge as a significant direct determinant of trust or value in the full models. Several interpretations are possible. First, in organizations where governance practices are relatively formalized, individual fears may be attenuated by controls, documentation, and verification routines. Second, aversion may manifest itself more strongly in experimental settings or when observing isolated errors, whereas our study captures more general and stabilized perceptions. This result therefore does not contradict Dietvorst et al. (2015), but suggests that behavioral effects may be dampened by institutional arrangements.

The result relating to overconfidence is more ambivalent. The positive effect of overconfidence on perceived value may appear counterintuitive in light of warnings about automation bias. It can nevertheless be understood if one considers that, in certain organizations, greater reliance on AI reduces frictions, accelerates processing, and gives actors a feeling of efficiency. In other words, overconfidence may be associated with immediately visible value for users, even if that value is potentially fragile or risky in the long run. This point echoes the work of Logg et al. (2019) on algorithm appreciation, while also reminding us, with Vasconcelos et al. (2023), that trust must remain calibrated. An organization may gain in apparent efficiency while simultaneously increasing its exposure to error if it follows recommendations without sufficient verification.

From a managerial perspective, the implications of the study are concrete. First implication: financial organizations have an interest in thinking jointly about data governance and AI governance. One without the other produces incomplete effects. High-quality data without AI governance may feed systems that are poorly monitored or poorly explainable. Conversely, ambitious AI governance built on weakly qualified data risks remaining ineffective. Second implication: governance arrangements must be connected to indicators of decision quality. Monitoring only the technical performance of models is not enough. It is also necessary to track processing times, the coherence of trade-offs, the quality of justifications, challenges to recommendations, and incidents of excessive reliance. Third implication: firms must invest in AI literacy, verification protocols, and human supervision proportionate to the level of risk.

This research nevertheless presents several limitations. The first lies in its cross-sectional design, which does not allow causal relationships to be established. The observed associations are compatible with the theoretical model, but longitudinal studies would be necessary to analyze the dynamics of trust and value over time. The second limitation concerns the perceptual nature of the measures. Value creation is assessed here as a perceived construct, and not through objective indicators such as ROI, fraud reduction, avoided losses, or productivity gains. The third limitation lies in the national and sectoral context: the Moroccan financial sector offers a relevant field, but the findings would gain from comparison with other institutional contexts or other emerging economies.

These limitations open stimulating research perspectives. Future work could test the model using objective performance and risk indicators, introduce moderating variables related to organizational culture, analytical maturity, or regulatory pressure, and conduct multi-group analyses across banks, insurance companies, and fintechs. It would also be useful to mobilize quasi-experimental designs or A/B tests to better isolate the effect of certain governance arrangements. Finally, the influence of cultural, normative, and relational factors on trust in AI deserves further examination, especially in African contexts, where digital transformation is combined with issues of institutional trust, inclusion, and digital sovereignty. Despite these limitations, the study provides a solid framework for understanding how governance, far from being a purely normative constraint, can become a genuine lever of value when it supports informed trust and high-quality decisions.

Beyond the strictly managerial implications, this research also calls for a broader reading of governance as a mechanism of organizational legitimation. In environments where AI intervenes in risk assessment, access to credit, anomaly detection, or offer personalization, the question is not only whether models are performant, but whether their uses can be justified, explained, and defended before stakeholders. The value created by AI should therefore not be reduced to productivity gains or cost reduction. It also includes institutional value, made up of compliance, credibility, risk control, and durable trust. This extension of the notion of value is particularly important in the financial field, where technologies are never neutral and where algorithmic decisions are embedded in relations of responsibility. In this sense, data governance and AI governance appear as conditions for the social and organizational acceptability of algorithmic devices, rather than as a simple layer of control added afterward.

7. Conclusion

This research aimed to examine how data governance and AI governance influence value creation in Moroccan financial organizations, while taking into account the mediating role of trust in AI and decision quality, as well as the influence of behavioral biases. The results obtained confirm that value does not emerge directly from AI systems, but from the articulation between governance arrangements, organizational trust, and the quality of managerial trade-offs.

More specifically, data governance and AI governance both strengthen trust in AI. This trust then improves decision quality, which constitutes the main explanatory channel of value creation. Data governance also retains a direct effect on value, which underlines its importance as a strategic infrastructure of performance. AI governance, for its part, acts mainly indirectly, by making systems more credible, more governable, and more integrable into decision routines.

The study also shows that behavioral biases should not be ignored. Algorithm aversion does not emerge as a major determinant in the full models, whereas overconfidence appears associated with higher perceived value, which invites the design of vigilance mechanisms and human supervision. The main managerial message is clear: the sustainable value of AI rests on calibrated trust, supported by high-quality data, explicit controls, and reflective organizational appropriation.

Overall, the article proposes an integrative reading of the relationship between governance and performance in data-intensive environments. In the case of the Moroccan financial sector, it appears that governing data and governing AI do not belong to a purely compliance-oriented logic, but rather constitute a genuine lever of value creation. It is this translation of governance into performance, through the intermediary of trust and decision quality, that represents the principal contribution of this research.

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