ALGORITHMIC TRUST, EXPLAINABILITY, AND CONTESTABILITY AS STRATEGIC CAPABILITIES IN BANKING: EMPIRICAL EVIDENCE FROM ROMANIA

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Abstract

This article presents the empirical findings of a primary survey conducted on a sample of 100 banking service consumers in Romania, analyzing three interconnected dimensions: comparative trust (human operator vs. AI system), perceived explainability of AI-based banking decisions, and perceived algorithmic control (accountability). The study connects consumer behavior research with strategic management theory, positioning these three dimensions as constituent elements of an emerging strategic capability—algorithmic governance—that drives competitive advantage in digitized banking markets. Building on the resource-based view, dynamic capabilities theory, and stakeholder capitalism frameworks, the article argues that banks' ability to build consumer trust through transparent and contestable AI systems constitutes a value-generating and hard-to-imitate organizational capability. Empirical results reveal a strong preference for human operators (77%), moderate uncertainty regarding AI decision transparency (mean Q1 = 3.94/7, not significantly different from the scale midpoint), and a strongly positive perceived contestability (mean Q2 = 5.59/7, with 75% of respondents clustered in the upper three scale positions)—indicating that Romanian banking consumers are broadly aware of their recourse rights, even as they remain skeptical of AI decision-making authority and uncertain about AI transparency. These findings carry direct implications for AI governance strategy, competitive positioning, and ESG alignment in the Romanian banking sector.

Keywords: *algorithmic trust, explainability, contestability, strategic capability, AI governance, dynamic capabilities, banking strategy.*

JEL Classification: *G21, M15, O33.*

1. Introduction

The integration of artificial intelligence into the banking sector has progressed from an experimental phase to a structural transformation of how financial institutions make decisions, manage risks, and interact with consumers. AI-based applications—from credit scoring and fraud prevention to customer behavior analysis and automated advisory services—have become deeply embedded in banking operations, often operating with limited interpretability and few avenues for consumer recourse (Pasquale, 2015; Glikson and Woolley, 2020). This shift raises questions that are simultaneously behavioral, ethical, and strategic: how do consumers perceive these systems, how much trust do they place in them compared to human operators, and—crucially—how do banks' choices regarding AI governance translate into competitive advantages or strategic vulnerabilities?

Strategic management theory has typically focused on resources, capabilities, and positioning at the enterprise level as the cornerstones of competitive advantage (Barney, 1991; Porter, 1985). The era of digital transformation has brought new levels of complexity: platform dynamics, competition within ecosystems, data-driven intellectual property, and AI-based decision-making architectures are now reshaping how value is created and captured (Iansiti and Lakhani, 2020; Teece et al., 1997). In this context, the governance of AI systems—including transparency, explainability, and consumer appeal mechanisms—is taking shape as a strategically relevant organizational capability, not merely a compliance requirement.

This article adds to both strands of the existing literature. First, it provides primary empirical evidence on consumer perceptions of AI in the Romanian banking sector through three survey dimensions: comparative trust between human and AI-based decision-makers (Q0), perceived explainability of AI-based banking decisions (Q1), and perceived algorithmic control—specifically, the capacity to challenge or request human review of automated decisions (Q2). Second, it integrates these findings into a strategic management framework, arguing that these consumer perceptions are not merely attitudinal data points, but indicators of strategic positioning and the maturity of banking institutions' governance.

The article is organized as follows: Section 2 provides a review of the relevant literature at the intersection of trust in AI and strategic management. Section 3 presents the methodology and data. Section 4 reports and analyzes the empirical results. Section 5 explores the implications for strategic management. Section 6 closes with research proposals and directions for future studies.

2. Literature Review

2.1. Consumer Trust in AI Banking Systems

Scientific research has approached trust in AI systems as a multi-layered phenomenon, integrating cognitive evaluations, emotional reactions, and behavioral intentions into a unified construct (Lee and See, 2004; Glikson and Woolley, 2020). In the banking context, consumer trust is of particular importance: algorithmic decisions on access to credit, fraud detection, or contractual terms directly affect consumer well-being and financial inclusion. The literature distinguishes between trust in the technology itself and trust in the institution implementing it—a critical distinction from an analytical perspective, as institutional trust can mitigate or amplify perceptions of AI systems (Siau and Wang, 2018; Lankton et al., 2015).

A recurring finding in empirical studies is that perceived explainability—the degree to which consumers understand how AI-based decisions are made—positively affects trust, but this relationship is moderated by context, digital literacy, and institutional credibility (Shin, 2021; Ribeiro et al., 2016). Equally important, and perhaps with a larger impact, is perceived algorithmic control: when consumers believe they can challenge, override, or obtain a human review of automated decisions, trust rises substantially (Binns et al., 2018; Kizilcec, 2016). The comparative dimension—whether humans or AI systems are more trustworthy as decision-makers—has received less empirical attention in Central and Eastern European contexts, despite its strategic importance for banks seeking to calibrate the appropriate degree of automation.

2.2. AI Governance as Strategic Capability

Strategic management literature offers multiple reference frameworks for understanding why AI governance is important from a competitive standpoint. The resource-based view (RBV) argues that sustainable competitive advantage rests on organizational resources that are strategically relevant, rare, difficult to imitate, and integrated into coordinated processes (VRIO) (Barney, 1991). Applied to AI governance, this framework suggests that banks that develop authentic, institutionally integrating capabilities for transparent and accountable AI—not merely compliance-oriented disclosures—possess a resource that is difficult to replicate. Consumer trust, built on authentic governance practices, constitutes an intangible asset of strategic value.

The theory of dynamic capabilities extends this logic by highlighting an organization's ability to identify changes in the external environment, act strategically, and reallocate its internal resources as needed (Teece et al., 1997). Against the rapidly evolving regulatory framework for AI—particularly with the adoption of the EU AI Act, which imposes new obligations on high-risk AI systems in the financial services sector—banks' dynamic algorithm governance capabilities determine their ability to adapt strategically without losing consumer trust or operational legitimacy (European Banking Authority, 2021). Banks that treat AI governance as a dynamic capability, rather than a static compliance exercise, will be better positioned to respond to regulatory changes and evolving consumer expectations.

The framework of stakeholder-oriented capitalism, formulated by Porter and Kramer (2011) and broadened by the integration of ESG criteria into corporate strategy, adds another dimension: AI governance is not solely a competitive variable, but also one linked to social responsibility and reputation. Banks that integrate responsibility, transparency, and consumer redress into their AI systems align their operational practices with ESG criteria, which are being increasingly scrutinized by investors, regulators, and consumers alike (Iansiti and Lakhani, 2020; Atz et al., 2023). In this regard, the governance of algorithmic systems is becoming a convergence point between strategic competitive positioning and value creation for stakeholders.

2.3. The Romanian Banking Context

Romania constitutes a specific case study from a contextual perspective for investigating trust in AI and governance in the banking sector. As demonstrated in the first article of this cumulative thesis (Mangiurea, 2025), Romania displays comparatively lower levels of consumer trust in algorithmic banking decisions, a higher perceived risk, and lower digital literacy compared to benchmarks in Western Europe, such as Germany (European Commission, 2023; Obelovska et al., 2025). These systemic features suggest that the strategic importance of algorithmic governance—and particularly of mechanisms for explainability and challengeability—can be amplified in the Romanian context, where deficits in institutional trust make the credibility of governance a particularly scarce and valuable resource.

The Romanian banking sector is experiencing a rapid integration of artificial intelligence, driven by the need for greater efficiency, competitive pressure from new entrants in the Financial Technology (FinTech) sector, and alignment with EU standards (EBA, 2021). In this context, primary data obtained from surveys on consumer perceptions provide fact-based information for strategic decision-making—both at the enterprise level (governance choices of individual banks) and at the institutional level (the development of regulations and supervisory frameworks).

3. Methodology

The empirically-based component of this article draws on a primary survey conducted among 100 banking service consumers in Romania. The survey was designed to capture consumers' perceptions across seven areas relevant to AI adoption and trust in the banking sector. This article focuses on three aspects selected for their theoretical consistency and strategic relevance:

Q0 (Comparative Trust): "When it comes to making decisions about banking, who do you trust more?"—with four response options (human operator, AI system, both equally, don't know). This item captures the comparative legitimacy attributed to human versus algorithmic decision-makers.

Q1 (Perceived Explainability): "It is clear to me how the bank decides when using AI."—measured on a 7-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree). This item operationalizes perceived transparency as defined in the XAI literature (Doshi-Velez and Kim, 2017; Shin, 2021).

Q2 (Perceived Algorithmic Control / Contestability): "I feel that I can contest or request a human review when an automated bank decision negatively affects me."—measured on a 7-point Likert scale. This item captures the procedural dimension of perceived control identified as a critical trust antecedent (Binns et al., 2018; Kizilcec, 2016).

The sample (n=100) was selected using convenience sampling, targeting Romanian banking service users aged 19 to 25 who have completed higher education and have recent experience using digital banking services. This demographic profile corresponds to the digital native generation, which is most directly exposed to AI-based banking interactions, making it theoretically relevant to the research questions at hand. Although not fully probability-based, the sample provides an initial empirical foundation for theoretical propositions and the development of the research agenda, in line with the design of exploratory doctoral research (Creswell, 2014; Saunders et al., 2019).

The statistical appropriateness of the sample was assessed through a post-hoc analysis of statistical power. For a conventional effect size (rho = 0.30), a sample of n = 100 achieves a statistical power of 0.862 at $\alpha = 0.05$, exceeding the standard threshold of 0.80 (Cohen, 1988). This confirms that the sample size is statistically robust and sufficient for the exploratory correlational analyses conducted in this study. For smaller effects (rho ≈ 0.16, as observed between Q1 and Q2), a sample size of approximately n = 294 would be required to achieve a power of 0.80, which underscores the exploratory nature of this study and the need for larger samples in subsequent confirmatory research.

The distribution characteristics of the items on the Likert scale were assessed using the Shapiro-Wilk and Kolmogorov-Smirnov tests prior to selecting the inferential procedures. Both Q1 ($W = 0.921$, $p < 0.001$; $D = 0.218$, $p < 0.001$) and Q2 ($W = 0.844$, $p < 0.001$; $D = 0.230$, $p < 0.001$) deviate significantly from normality, justifying the use of nonparametric procedures. Therefore, bivariate associations were examined using Spearman's rank correlation coefficient, which is appropriate for ordinal Likert data (Field, 2018). One-sample t-tests were used to compare item means with the scale mean (4.0), with Cohen's d reported as a standardized measure of effect size. For the nominally scaled item Q0, a chi-square goodness-of-fit test was applied to evaluate whether the observed distribution of trust preferences differed significantly from a random distribution, using Cramér's V as an indicator of effect size. Descriptive statistics are presented for all items on the Likert scale, including the mean, standard deviation, median, skewness, kurtosis, and 95% confidence intervals.

4. Empirical Findings

4.1. Q0 – Comparative Trust: Human Operator vs. AI System

Table 1 displays the distribution of responses to question Q0. The results reveal a strong and statistically significant preference for human operators in banking decision-making contexts, with 77% of respondents expressing greater confidence in human operators than in AI systems (9%). A moderate proportion (13%) indicated equal trust in both, and only one respondent declined to express a preference. A chi-square goodness-of-fit test confirmed that this distribution deviates significantly from random: $\chi^2(3) = 147.200$, $p < 0.001$, Cramér's $V = 0.700$ (large effect). The dominance of the preference for the human operator is therefore not a sampling artifact, but a statistically robust finding.

Table no. 1 Chi-Square Goodness-of-Fit: Q0 – Comparative Trust in Banking Decisions (n=100)

Response Option	Observed (n)	Expected (n)	%	Residual
A human operator	77	25	77%	+52
An AI system	9	25	9%	−16
I trust both equally	13	25	13%	−12
Don't know / Cannot assess	1	25	1%	−24
Total	100	100	100%	—

Note. Expected frequencies based on uniform distribution (n/k = 25 per category). Source: Author's primary survey data, n=100.

Table no. 2 Q0 – Comparative Trust in Human Operators vs. AI Systems (n=100)

Response Option	Count	Percentage
A human operator	77	77%
An artificial intelligence system	9	9%
I trust both equally	13	13%
Don't know / Cannot assess	1	1%
Total	100	100%

Source: Author's primary survey data, n=100.

The 77% to 9% ratio constitutes a significant asymmetry in terms of trust, which has direct strategic implications. From a behavioral strategy perspective, this finding indicates that the current trajectory of AI adoption in the Romanian banking sector faces a fundamental legitimacy challenge: most consumers have not yet internalized AI systems as credible and trustworthy decision-makers comparable to human professionals. This asymmetry is consistent with findings from the broader academic literature in Central and Eastern Europe, which documents a lower level of institutional trust and higher skepticism toward AI compared to Western European markets (European Commission, 2023; World Bank, 2021).

From a strategic perspective, this suggests that banks that position AI systems as a complement to human judgment—rather than a replacement for it—could enjoy greater acceptance among consumers. The 13% who express equal trust in both represent a segment already aligned with hybrid decision-making architectures that combine human and AI collaboration, which could constitute an early-adopting group for advanced AI-based banking services.

4.2. Q1 – Perceived Explainability of AI Banking Decisions

Table 4 presents the distribution of Q1 responses. Descriptive statistics indicate a mean of 3.94 (SD=1.377, Median=4.0, 95% CI [3.667, 4.213]), confirming that the average respondent is positioned close to the scale midpoint with moderate uncertainty about AI decision transparency. A one-sample t-test against the midpoint (4.0) revealed no statistically significant difference: $t(99) = -0.436$, $p = .664$, Cohen's $d = -0.044$ (negligible effect). This means that, as a group, Romanian banking consumers neither clearly agree nor disagree that bank AI decisions are transparent to them — a finding that itself carries strategic significance. The distribution shows mild negative skewness (skewness = −0.265) and near-mesokurtic shape (excess kurtosis = 0.271), with the Shapiro-Wilk test confirming non-normality ($W=.921$, $p<.001$).

Table no. 3 Descriptive Statistics for Q1 and Q2 (n=100)

Item	Mean	SD	Mdn	Skew	Kurt	95% CI
Q1 – Perceived Explainability	3.940	1.377	4.0	−0.265	0.271	[3.667, 4.213]
Q2 – Algorithmic Control (Contestability)	5.590	1.485	6.0	−0.837	0.079	[5.295, 5.885]

Note. Mdn = Median. 95% CI = 95% confidence interval for the mean. Scale range: 1–7. Source: Author's primary survey data.

Table no. 4 Q1 – Perceived Explainability: "It is clear to me how the bank decides when using AI" (n=100)

Scale (1=Strongly Disagree, 7=Strongly Agree)	Count	%
1 – Strongly Disagree	8	8%
2	5	5%
3	17	17%
4 – Neutral	38	38%
5	23	23%
6	5	5%
7 – Strongly Agree	4	4%

Source: Author's primary survey data, n=100.

The distribution is notably concentrated around the neutral-to-moderately-positive range, with 38% selecting scale point 4 (neutral) and 23% selecting scale point 5. This bunching around the midpoint suggests widespread uncertainty rather than a bimodal distribution of clearly informed versus clearly uninformed consumers. Only 9% strongly agreed (scores 6–7) that bank AI decisions are clear to them, while 30% expressed clear disagreement (scores 1–3).

This pattern aligns with the theoretical prediction that technical explainability — even where formally mandated — does not automatically translate into perceived consumer clarity. The gap between regulatory compliance (e.g., GDPR Article 22 right to explanation) and actual consumer comprehension is empirically visible in this distribution. From a dynamic capabilities perspective, banks face a sensing gap: they may not fully perceive the extent to which their current explainability practices fail to generate genuine consumer understanding, representing an organizational capability deficit with competitive consequences.

4.3. Q2 – Perceived Algorithmic Control (Contestability)

Table no. 5 Normality Tests for Q1 and Q2

Item	SW: W	SW: p	KS: D	KS: p	Result
Q1 – Perceived Explainability	.9208	< .001	.2175	< .001	Non-normal
Q2 – Algorithmic Control	.8442	< .001	.2301	< .001	Non-normal

Note. SW = Shapiro-Wilk; KS = Kolmogorov-Smirnov. Both items deviate significantly from normality (α = .05), justifying non-parametric inferential procedures.

Table 6 presents the distribution of Q2 responses. Descriptive statistics reveal a mean of 5.59 (SD=1.485, Median=6.0, 95% CI [5.295, 5.885]), substantially above the scale midpoint. A one-sample t-test confirmed that the mean is significantly higher than 4.0: $t(99) = 10.710$, $p < .001$, Cohen's $d = 1.071$ (large effect). The distribution is strongly negatively skewed (skewness = −0.837), with Shapiro-Wilk confirming non-normality ($W=.844$, $p<.001$). All 100 respondents provided a valid answer, and 75% are clustered in the upper three positions of the scale (scores 5–7): 40% selected scale point 7 (Strongly Agree), 17% selected scale point 6, and 18% selected scale point 5. Only 9% expressed disagreement (scores 1–3), with no responses at scale point 2.

Table no. 6 Q2 – Perceived Algorithmic Control: "I feel I can contest or request human review of automated bank decisions" (n=100)

Scale (1=Strongly Disagree, 7=Strongly Agree)	Count	%
1 – Strongly Disagree	2	2%
2	0	0%
3	7	7%
4 – Neutral	16	16%
5	18	18%
6	17	17%
7 – Strongly Agree	40	40%

Source: Author's primary survey data, n=100.

This distribution is strongly negatively skewed (skewness = −0.837), with 75% of respondents concentrated in the upper three positions of the scale (scores 5, 6, and 7). The mean score is 5.59 (SD=1.485, 95% CI [5.295, 5.885]), indicating that Romanian banking consumers generally believe they retain the ability to contest automated decisions or request human review. Notably, scale point 2 received zero responses, and only 9% of respondents expressed disagreement (scores 1–3), suggesting that skepticism about contestability is marginal in this sample.

Interpreted alongside Q0 and Q1, this pattern reveals an interesting divergence in consumer perceptions. Respondents are simultaneously skeptical of AI decision-making authority (Q0: 77% prefer human operators), uncertain about the transparency of AI processes (Q1: mean 3.94, clustered around neutral), yet broadly confident that recourse mechanisms exist (Q2: mean 5.59, strongly skewed toward agreement). This divergence may reflect awareness of regulatory rights — such as the EU AI Act's human oversight provisions and GDPR Article 22 — without necessarily having direct personal experience with contestation procedures. In other words, consumers know they are entitled to contest decisions, but remain skeptical about the quality and fairness of the AI systems making those decisions in the first place.

Table no. 7 Spearman Rank-Order Correlation Matrix (Q1–Q6, n=100)

Item	Q1	Q2	Q3	Q4	Q5	Q6
Q1 – Explainability	—	.163	.307**	−.032	.160	.137
Q2 – Ctrl/Contestab.	.163	—	.238*	.046	.214*	.124
Q3 – Autonomy	.307**	.238*	—	.109	.382***	.280**
Q4 – Perceived Risk	−.032	.046	.109	—	.219*	−.023
Q5 – Instit. Trust	.160	.214*	.382***	.219*	—	.240*
Q6 – Behav. Intention	.137	.124	.280**	−.023	.240*	—

*Note. *p < .05, **p < .01, ***p < .001 (two-tailed, n=100). Source: Author's primary survey data.*

From a strategic governance perspective, the high perceived contestability scores are encouraging but must be interpreted cautiously. Consumer confidence in recourse mechanisms may be grounded in regulatory awareness rather than actual experience with bank-specific complaint channels. This creates a strategic risk: if consumers who believe they can contest decisions subsequently find the process opaque or ineffective, the resulting trust violation may be disproportionately damaging. Banks that invest in making contestation processes genuinely accessible, visible, and responsive will not only meet regulatory obligations but convert a perceived right into a concrete trust-building mechanism — a governance capability with direct and measurable commercial value.

Given the confirmed non-normality of all Likert-scaled items, bivariate associations were examined using Spearman's rank-order correlation across all six survey dimensions. The analysis yields several theoretically significant findings. First, the correlation between Q1 (perceived explainability) and Q2 (perceived contestability) is small and non-significant: rho(98) = .163, p = .105. This finding is substantively important: it indicates that transparency and control are perceived as independent rather than interdependent dimensions of algorithmic governance in the Romanian banking context. Consumers who understand how bank AI decisions are made do not necessarily feel more empowered to contest them, and vice versa. This independence suggests that banks must address explainability and contestability as distinct governance challenges, not as a unified intervention.

Second, Q3 (decision autonomy — comfort with delegating decisions to AI) emerges as the most central item in the correlation structure, showing significant positive associations with Q1 (rho = .307, p = .002), Q2 (rho = .238, p = .017), Q5 (rho = .382, p < .001), and Q6 (rho = .280, p = .005). This suggests that willingness to delegate decisions to AI systems is coherently linked to perceived transparency, contestability, institutional trust, and behavioral intention. Third, Q4 (perceived risk) shows no significant correlation with Q1 (rho = −.032, p = .751) or Q2 (rho = .046, p = .647), indicating that risk perceptions operate independently of transparency and control perceptions — a finding that challenges simplified governance models assuming that increased transparency automatically reduces perceived risk.

Internal consistency analysis using Cronbach's α confirms that the six items do not form a unidimensional scale (α = .587), consistent with the multidimensional theoretical framework underlying the instrument. This is expected and appropriate for an exploratory survey measuring conceptually distinct constructs. Post-hoc power analysis confirms that n = 100 achieves adequate power (.862) for detecting medium-sized correlations (rho = .30) at α = .05, validating the statistical stability of the sample for the analyses conducted.

These findings carry direct theoretical relevance. The independence of Q1 and Q2 challenges the assumption, common in the XAI literature, that explainability and perceived control are always co-constructed (Shin, 2021; Binns et al., 2018). In the Romanian banking context, the two dimensions appear to operate through distinct psychological mechanisms, implying that separate governance interventions are needed to address each. The strong centrality of Q3 (autonomy) further suggests that consumers' willingness to delegate decisions to AI may serve as a meaningful mediating construct between transparency/control perceptions and behavioral intentions — a relationship worthy of further empirical investigation in the comparative CEE study planned in subsequent phases of this cumulative dissertation.

Table no. 8 One-Sample t-Tests Against Scale Midpoint (4.0) for Q1 and Q2

Item	M (SD)	t(99)	p	d	95% CI
Q1 – Perceived Explainability	3.94 (1.38)	−0.436	.664	−0.044	[3.667, 4.213]
Q2 – Algorithmic Control	5.59 (1.49)	10.710	< .001	1.071	[5.295, 5.885]

Note. d = Cohen's d. Tests compare each item mean against the theoretical midpoint (4.0). Q1 does not differ significantly from midpoint; Q2 is significantly above midpoint (large effect).

4.4. Gender-Based Comparisons

The dataset includes 41 male (41%) and 59 female (59%) respondents, all aged 19–25 with completed higher education. To explore whether gender moderates the key attitudinal dimensions, a Chi-Square Test of Independence (Gender × Q0) and Mann–Whitney U tests (Gender × Q1; Gender × Q2) were conducted, consistent with the non-parametric analytical framework established in Section 3.

For Q0 (comparative trust), the Chi-Square test conducted in SPSS revealed a statistically significant association between gender and trust preference: $\chi^2(3) = 11.432$, $p = .010$, Cramér's V = .338, indicating a moderate effect. Table 9 presents the frequency distribution by gender, and Figure 1 displays the SPSS Crosstabs output. Female respondents show a higher proportion trusting AI systems exclusively (11.9% vs. 4.9% for males) and a higher proportion expressing equal trust in both (16.9% vs. 7.3%), while male respondents show a slightly stronger concentration of trust in human operators (82.9% vs. 72.9%). These patterns suggest that female respondents in this cohort display a marginally more open orientation toward AI-based decision-making, though the majority of both groups continue to favour human operators. It should be noted that 4 cells (50.0%) had expected counts below 5 (minimum expected count = .40), which warrants cautious interpretation of this result; the finding should be replicated with a larger and more balanced sample.

Table no. 9 Chi-Square Test of Independence: Gender × Q0 – Comparative Trust (n=100)

Response Option	Male (n=41)	Female (n=59)	Total (n)	%
A human operator	34 (82.9%)	43 (72.9%)	77	77%
An AI system	2 (4.9%)	7 (11.9%)	9	9%
I trust both equally	3 (7.3%)	10 (16.9%)	13	13%
Don't know / Cannot assess	2 (4.9%)	0 (0.0%)	1	1%

$\chi^2(3) = 11.432$, $p = .010$, Cramér's V = .338 (moderate effect). Source: SPSS Crosstabs output. Note: 4 cells (50.0%) have expected count less than 5; results should be interpreted with caution.

Crosstabs

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
Gender * Comparative trust (numeric)	100	100.0%	0	0.0%	100	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	11.432[a]	3	.010
Likelihood Ratio	11.705	3	.008
Linear-by-Linear Association	1.392	1	.238
N of Valid Cases	100		

a. 4 cells (50.0%) have expected count less than 5. The minimum expected count is .40.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.338	.010
	Cramer's V	.338	.010
N of Valid Cases		100	

Figure 1. SPSS Crosstabs Output: Chi-Square Test of Independence, Gender x Q0 (Comparative Trust). Source: IBM SPSS Statistics, generated from primary survey data (n=100).

For Q1 (perceived explainability) and Q2 (perceived algorithmic control/contestability), Mann–Whitney U tests revealed no statistically significant gender differences. For Q1: U = 1272.5, z = 0.442, p = .649, r = .044 (negligible effect). For Q2: U = 1218.5, z = 0.063, p = .950, r = .006 (negligible effect). Median scores were identical across genders for both dimensions (Q1 Mdn = 4.0 for both; Q2 Mdn = 6.0 for both), indicating that perceptions of AI transparency and contestability in this cohort are gender-neutral. This finding suggests that governance-oriented interventions aimed at improving explainability and consumer control do not need to be gender-differentiated for this population segment.

Table no. 10 Mann–Whitney U Tests: Gender Differences in Q1 and Q2 (n=100)

Item	Male M (SD)	Female M (SD)	U	z	p	r
Q1 – Perceived Explainability	4.05 (1.40)	3.86 (1.37)	1272.5	0.442	.649	.044
Q2 – Algorithmic Control	5.61 (1.53)	5.58 (1.46)	1218.5	0.063	.950	.006

Note. r = z / √N (effect size). Neither Q1 nor Q2 shows a statistically significant difference by gender (p > .05). Male: n=41; Female: n=59.

Taken together, the gender-based analysis reveals a nuanced pattern: while comparative trust orientations (Q0) show a statistically significant gender effect, the substantive perceptions of AI governance quality (Q1 and Q2) do not differ by gender. This implies that the trust gap between human and AI operators is partially gender-moderated, whereas the underlying governance dimensions — transparency and contestability — are perceived similarly across genders. Future research with larger samples and explicit gender stratification should examine whether this pattern holds across different CEE contexts.

5. Strategic Management Implications

5.1. Algorithmic Governance as a VRIO Capability

The empirical findings, viewed through the VRIO framework (Barney, 1991), suggest that algorithmic governance — the organizational capacity to make AI systems transparent, explainable, and contestable in ways that consumers actually perceive and value — constitutes a potentially sustainable source of competitive advantage in Romanian banking. The value criterion is met: as Q0 and Q1 demonstrate, trust deficits and explainability gaps are strategically costly, translating into consumer preference for human operators and uncertainty about AI processes. The rarity criterion is plausible: given that most banks are at similar early stages of explainability practice, genuine governance capability is not yet widely distributed. The inimitability criterion is supported by the observation that trust-building through governance is path-dependent and rooted in institutional credibility — a resource built over time through consistent behavior, not purchased or replicated quickly. Organization is the variable under strategic control: banks must align governance structures, communication strategies, and operational practices to convert AI capabilities into trust outcomes.

Table 11 maps the three survey dimensions to their respective strategic management frameworks, illustrating how empirical findings connect to theoretical concepts from the course curriculum on strategic management in the digital era.

Table no. 11 Mapping Survey Dimensions to Strategic Management Frameworks

Survey Dimension	Strategic Management Concept	Theoretical Framework
Q0 – Comparative Trust (Human vs. AI)	AI vs. human decision-making in strategy; legitimacy of algorithmic authority	Behavioral strategy theory; AI-enabled decision architectures (Iansiti and Lakhani, 2020)
Q1 – Perceived Explainability	Transparency as a governance capability; XAI as institutional resource	Resource-Based View (Barney, 1991); Dynamic capabilities (Teece et al., 1997)
Q2 – Algorithmic Control (Contestability)	Consumer control mechanisms as strategic differentiator; accountability frameworks	Stakeholder capitalism; ESG governance; Porter's value chain (Porter, 2021)

Source: Author's own synthesis based on theoretical frameworks reviewed in Section 2.

5.2. Dynamic Capabilities and the AI Governance Sensing Gap

The moderate explainability scores (Q1: M=3.94, SD=1.377) reveal a sensing gap in Romanian banks' dynamic capabilities: institutions are not adequately detecting or responding to consumer uncertainty about how AI decisions are made. Dynamic capabilities theory (Teece et al., 1997) prescribes three sequential activities — sensing environmental signals, seizing strategic opportunities, and reconfiguring organizational assets. The bivariate analysis reinforces this finding: the statistical independence of Q1 and Q2 (rho=.163, p=.105) indicates that perceived transparency and perceived control represent separate governance deficits requiring distinct institutional responses. Meanwhile, the divergence between high contestability confidence (Q2: M=5.59, SD=1.485) and low-to-neutral explainability (Q1: M=3.94) signals that Romanian banking consumers are aware of their procedural rights but remain uninformed about the substantive logic of AI decisions — a gap that banks have yet to strategically address.

Seizing the opportunity implied by these gaps would involve reconfiguring communication strategies, digital interface design, and customer service protocols to make AI decision logic more accessible and human review pathways more visible. These reconfigurations are not merely operational improvements; they constitute capability upgrades that position the institution differently in the consumer trust landscape — a landscape that, given regulatory trends, will become an increasingly important competitive battlefield.

5.3. ESG Integration and Stakeholder Strategy

The AI governance dimensions measured in this survey are directly relevant to ESG-aligned strategy, a topic central to contemporary strategic management. The 'G' pillar of ESG — governance — encompasses the accountability frameworks, audit mechanisms, and redress channels that determine whether organizational power is exercised responsibly. AI systems in banking that operate without adequate consumer transparency or contestation rights represent governance deficits that, under emerging EU reporting standards, will require disclosure and remediation.

From a stakeholder capitalism perspective (Porter and Kramer, 2011), banks that proactively invest in algorithmic transparency and consumer empowerment are not only managing regulatory risk but creating shared value: consumers gain more control and understanding, while banks gain trust, loyalty, and reputational capital. The 13% of Q0 respondents who already trust both human and AI operators equally may represent the early-adopter segment of this value-creation dynamic — consumers who, through positive AI governance experiences, have updated their trust orientation in ways that facilitate deeper engagement with AI-driven services.

5.4. Competitive Strategy Implications for Romanian Banking

The combined profile from Q0, Q1, and Q2 suggests that Romanian banks operate in a trust-constrained AI market: consumers are skeptical of AI operators, uncertain about AI transparency, and either uninformed or ambivalent about their contestation rights. This context creates a strategic differentiation opportunity for institutions willing to invest in governance credibility. In Porter's (1985) terms, a differentiation strategy built on trust, transparency, and consumer empowerment is feasible and defensible in this market context — precisely because it is rare, difficult to imitate, and directly aligned with consumer preference signals revealed by the data.

Conversely, banks that pursue AI cost leadership strategies without investing in governance infrastructure risk creating reputational liabilities that undermine long-term competitive positioning, particularly as regulatory scrutiny intensifies and ESG investor criteria become more granular with respect to algorithmic accountability.

6. Research Propositions and Future Directions

Based on the empirical findings and theoretical integration developed in this article, the following research propositions are advanced for future investigation:

P1: Banks with higher perceived explainability (Q1 scores) will exhibit higher consumer retention rates for AI-based services, mediated by consumer trust, after controlling for digital literacy and prior banking experience.

P2: The institutionalization of visible human review mechanisms (Q2 awareness) will have a stronger positive effect on consumer trust in AI banking systems than technical explainability disclosures alone, consistent with the prediction that perceived control is a more robust trust predictor than perceived transparency.

P3: The competitive differentiation value of algorithmic governance capabilities (VRIO) will be greater in markets with lower baseline institutional trust (such as Romania) than in markets with higher institutional trust (such as Germany), amplifying the strategic return on governance investment in CEE contexts.

P4: Banks that integrate AI governance performance into their ESG reporting frameworks will achieve superior reputational capital outcomes, as measured by consumer trust indices and regulatory compliance assessments, compared to banks that treat AI governance as a purely technical compliance matter.

P5: The 77% preference for human operators (Q0) will moderate the relationship between AI service quality and consumer adoption intentions, such that even superior AI performance may not overcome trust deficits in the absence of visible human oversight assurance mechanisms.

These propositions constitute a research agenda linking behavioral consumer data with strategic management theory — a contribution positioned at the intersection of strategic cognition, digital transformation governance, and stakeholder value creation that this cumulative thesis will further develop through comparative CEE empirical analysis.

7. Conclusions

This article has made two interconnected contributions. Empirically, it provides primary survey evidence from Romania documenting that: (1) 77% of banking consumers express greater trust in human operators than in AI systems for banking decisions, representing a significant legitimacy gap for AI-driven services; (2) perceived explainability of bank AI decisions is moderate and skewed toward uncertainty, with an average score near the midpoint of the 7-point scale (M = 3.94) and only 9% of respondents strongly affirming that AI decision logic is clear to them; and (3) perceived contestability is strongly positive and right-skewed, with 75% of respondents clustered in the upper three positions of the scale (M = 5.59) and 40% selecting the maximum score — indicating that Romanian banking consumers broadly believe they retain the ability to contest or request human review of automated decisions, even as they remain skeptical of AI decision-making authority and uncertain about AI transparency.

From a theoretical perspective, the article positioned these empirical findings within a strategic management framework, arguing that algorithmic governance — the organizational capacity to make AI transparent, explainable, and contestable in ways that generate genuine consumer trust — constitutes a strategic resource that satisfies VRIO criteria in digitalized banking markets. This capability creates value (trust deficits are commercially costly and consumer skepticism toward AI operators is empirically documented), is potentially rare (few banks have moved beyond compliance-level governance toward genuine institutional embedding), is difficult to imitate (trust-building is path-dependent and rooted in accumulated institutional credibility), and is organizationally developable (governance structures, communication strategies, and interface design are within management's direct control). The article further demonstrates that AI governance is not only a competitive variable but also a stakeholder strategy imperative aligned with ESG, connecting the operational management of algorithmic systems to broader discussions on corporate accountability, shared value creation, and long-term institutional legitimacy. For the Romanian banking sector, where institutional trust deficits amplify the strategic importance of governance credibility, these implications are particularly salient.

The limitations of this study are acknowledged: the convenience sample of 100 respondents, the cross-sectional design, and the focus on a single country limit generalizability. Future research should replicate and extend these findings through stratified probability sampling, longitudinal designs, and comparative analyses of Central and Eastern European countries — in line with the broader methodological agenda of this cumulative doctoral dissertation.

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