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The Inclusion–Risk Paradox in FinTech and InsurTech: Effects of Algorithmic Access Expansion, Opacity, and Regulatory Safeguards

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Abstract

The rapid diffusion of FinTech and InsurTech has reconfigured the delivery of financial and insurance services through algorithmic decision systems that simultaneously expand access and introduce new forms of institutional risk. While prior studies largely examine financial inclusion or risk in isolation, limited empirical work has investigated their coexistence within a single analytical framework. This study addresses this gap by examining the inclusion–risk paradox in FinTech and InsurTech systems, focusing on the effects of algorithmic access expansion, algorithmic opacity, and regulatory safeguards on financial and insurance inclusion and institutional vulnerability. Anchored in institutional theory and algorithmic governance perspectives, the study employs a quantitative, survey-based research design using data collected from senior banking executives, FinTech leaders, and InsurTech decision-makers in regulated financial institutions in the Philippines. Structural equation modeling is applied to test direct and moderating relationships, with rigorous validity and reliability assessments conducted to ensure measurement robustness. The results indicate that algorithmic access expansion significantly enhances financial and insurance inclusion, while algorithmic opacity increases institutional vulnerability. Regulatory safeguards are found to play a critical moderating role by strengthening inclusion outcomes and attenuating risk amplification. These findings empirically validate the inclusion–risk paradox and contribute to the literature by integrating inclusion and institutional vulnerability within a unified model. The study offers policy-relevant insights for regulators and industry leaders seeking to balance innovation-driven inclusion with institutional resilience in AI-enabled financial systems.

Keywords: FinTech; InsurTech; algorithmic access expansion; algorithmic opacity; regulatory safeguards; financial inclusion; insurance inclusion; institutional vulnerability; inclusion–risk paradox; algorithmic governance

1. INTRODUCTION

The rapid diffusion of financial technology (FinTech) and insurance technology (InsurTech) has fundamentally transformed the architecture of financial service delivery through the integration of algorithmic decision systems. Artificial intelligence, machine learning, and data-driven analytics are now embedded in core banking and insurance processes, including credit scoring, underwriting, fraud detection, and claims management. These technologies are widely promoted as mechanisms for expanding access to financial and insurance services by reducing transaction costs, automating risk assessment, and overcoming informational frictions [1], [2], [3].

In emerging economies, algorithmic financial systems play a particularly prominent role in advancing national inclusion agendas. Digital payments, mobile banking platforms, and algorithmic credit and insurance models have expanded participation among previously underserved populations, including informal workers, micro-entrepreneurs, and first-time users of formal financial services [4], [5], [6]. Empirical evidence suggests that algorithmic access expansion is positively associated with increased account ownership, credit access, and insurance uptake, supporting claims that FinTech and InsurTech innovations contribute to inclusive economic development [7], [8].

Despite these inclusion gains, a growing body of literature cautions that algorithmic financial systems simultaneously introduce new forms of institutional vulnerability. Algorithmic decision models are frequently characterized by opacity arising from technical complexity, proprietary design, and limited explainability, which constrain effective oversight and accountability [9], [10]. Such opacity complicates internal governance, regulatory supervision, and risk management, particularly when algorithmic systems are deployed at scale across interconnected financial institutions [11], [12]. As a result, institutions may experience heightened operational, compliance, and systemic risk alongside expanded service access.

This coexistence of inclusion gains and risk amplification gives rise to what this study conceptualizes as the **inclusion–risk paradox**. Rather than representing a linear trade-off, inclusion and institutional vulnerability emerge as parallel outcomes of algorithmic financial innovation. Prior studies have typically examined financial inclusion or institutional risk in isolation, thereby obscuring their interdependence within digitally mediated financial systems [13], [14]. The limited empirical integration of these outcomes represents a significant gap in FinTech and InsurTech research.

Regulatory safeguards constitute a critical mechanism for mediating this paradox. Prudential regulation, consumer protection rules, algorithmic accountability requirements, and supervisory technologies are designed to align technological innovation with financial stability and institutional resilience [15], [16]. However, regulatory responses often lag behind technological adoption, particularly in emerging markets where supervisory capacity and institutional coordination remain uneven [17], [18]. Weak or fragmented safeguards may allow algorithmic opacity to persist, thereby amplifying institutional vulnerability even as inclusion expands.

Institutional theory provides a useful analytical lens for understanding these dynamics. Financial institutions operate under coercive, normative, and mimetic pressures that shape technology adoption and governance practices [19]. As banks and insurers adopt algorithmic systems to maintain legitimacy and competitiveness, they may converge toward similar technological configurations, diffusing both inclusion benefits and systemic risks across the sector [20]. In this context, algorithmic systems function not merely as technical tools but as quasi-institutional mechanisms that reshape authority, accountability, and risk distribution within financial organizations.

The Philippines offers a salient empirical context for examining the inclusion–risk paradox. National initiatives promoting digital payments, digital banking, and inclusive finance have accelerated the adoption of FinTech solutions, while InsurTech applications remain emergent but rapidly expanding [21], [22]. The increasing reliance on algorithmic systems within Philippine financial institutions has heightened both inclusion potential and governance complexity, making the setting particularly suitable for investigating how algorithmic access expansion, opacity, and regulatory safeguards interact.

Against this backdrop, this study addresses the following primary research question:

How do algorithmic access expansion, algorithmic opacity, and regulatory safeguards affect financial and insurance inclusion and institutional vulnerability in FinTech and InsurTech systems?

To answer this question, the study employs a quantitative, survey-based research design using data collected from senior banking executives, FinTech leaders, and InsurTech decision-makers in regulated financial institutions in the Philippines. Structural equation modeling is applied to test the direct effects of algorithmic access expansion and opacity, as well as the moderating role of regulatory safeguards, with rigorous validity and reliability procedures implemented.

This study contributes to the literature in three important ways. First, it empirically formalizes the inclusion–risk paradox by integrating inclusion and institutional vulnerability within a single analytical framework. Second, it extends institutional and algorithmic governance theory by demonstrating how algorithmic systems simultaneously enable access and generate institutional risk. Third, it provides policy-relevant evidence for regulators and industry leaders seeking to balance innovation-driven inclusion with institutional resilience in AI-enabled financial systems.

1.1. Research Questions

The increasing integration of algorithmic systems in FinTech and InsurTech environments has generated simultaneous gains in financial and insurance inclusion and emerging forms of institutional vulnerability. While algorithmic access expansion has been widely associated with improved outreach and participation, concerns persist regarding opacity, governance gaps, and risk amplification in digitally mediated financial systems.

To empirically examine this inclusion–risk paradox, this study is guided by the following research questions:

RQ1: How does algorithmic access expansion affect financial and insurance inclusion in FinTech and InsurTech systems?

RQ2: What is the effect of algorithmic opacity on institutional vulnerability within algorithmically mediated financial and insurance institutions?

RQ3: How do regulatory safeguards directly influence financial and insurance inclusion and institutional vulnerability in FinTech and InsurTech environments?

RQ4: Do regulatory safeguards moderate the relationship between algorithmic access expansion and financial and insurance inclusion?

RQ5: Do regulatory safeguards moderate the relationship between algorithmic opacity and institutional vulnerability?

Collectively, these research questions are designed to capture the dual outcomes of algorithmic financial innovation and to empirically assess the role of regulatory safeguards in shaping inclusion and risk dynamics within FinTech and InsurTech ecosystems.

1.2. Literature Review

1.2.1. FinTech and InsurTech as Algorithmic Financial Systems

FinTech and InsurTech represent a structural shift in financial intermediation in which algorithmic systems increasingly mediate access, pricing, and risk allocation. Unlike earlier forms of digitization that focused primarily on service delivery channels, contemporary FinTech and InsurTech platforms embed artificial intelligence, machine learning, and data analytics directly into core decision-making processes such as credit scoring, underwriting, fraud detection, and claims management [1], [2]. These technologies are commonly framed as efficiency-enhancing mechanisms capable of reducing transaction costs and overcoming information asymmetries in financial markets [3], [4].

Empirical studies demonstrate that FinTech adoption is positively associated with expanded access to formal financial services, particularly in emerging economies. Digital payments, mobile banking platforms, and platform-based credit systems have increased participation among previously underserved populations, including informal workers and micro-entrepreneurs [5], [6], [7]. Similarly, InsurTech innovations leveraging automated underwriting and digital distribution channels have been shown to improve insurance penetration by simplifying enrollment processes and enabling product customization [8], [9].

However, recent scholarship emphasizes that FinTech and InsurTech should be understood not merely as technological innovations but as **algorithmic financial systems** that reshape institutional governance, accountability, and risk distribution [10], [11]. This perspective highlights the need to evaluate inclusion outcomes alongside institutional and systemic consequences.

1.2.2. Algorithmic Access Expansion and Financial and Insurance Inclusion

Algorithmic access expansion refers to the use of automated decision systems and alternative data sources to broaden eligibility for financial and insurance services. Research indicates that algorithmic credit scoring models enable financial institutions to assess borrowers with limited or no formal credit histories, thereby expanding access to loans and digital financial products [12], [13]. In insurance markets, algorithmic underwriting and claims automation reduce administrative frictions and allow insurers to reach low-income and geographically dispersed populations [14], [15].

While these developments contribute to measurable inclusion gains, scholars caution that algorithmic inclusion is not inherently neutral or stable. Algorithmic systems often rely on behavioral and transactional proxies derived from digital footprints, which may embed structural biases and produce uneven inclusion outcomes across demographic groups [16], [17]. Moreover, inclusion achieved through algorithmic models may be conditional and reversible, as access can be rapidly withdrawn when data signals change or models are recalibrated [18].

These findings suggest that access expansion through algorithmic systems must be evaluated in relation to institutional governance and risk management rather than treated as an unambiguously positive outcome.

1.2.3. Algorithmic Opacity and Institutional Vulnerability

Algorithmic opacity constitutes a central challenge in FinTech and InsurTech governance. Opacity arises from the complexity of machine learning models, proprietary system design, and organizational practices that limit transparency and explainability [19], [20]. As algorithmic decision systems become more complex, it becomes increasingly difficult for institutions, regulators, and customers to understand how outcomes are generated or to contest adverse decisions [21].

Institutional vulnerability emerges when opacity undermines effective oversight and accountability. Financial institutions relying on opaque algorithmic systems face heightened exposure to model risk, compliance failures, and reputational damage [22], [23]. In insurance contexts, opaque underwriting models may distort risk pooling mechanisms and exacerbate adverse selection, posing long-term threats to institutional solvency [24], [25].

Empirical evidence suggests that excessive reliance on algorithmic systems can generate non-linear risk effects. Studies indicate that moderate adoption of financial technologies improves institutional performance, whereas extensive automation without adequate governance increases operational and systemic risk [26], [27]. These findings position algorithmic opacity as a structural driver of institutional vulnerability rather than a purely technical limitation.

1.2.4. Regulatory Safeguards and Algorithmic Governance

Regulatory safeguards play a critical role in shaping the outcomes of algorithmic financial systems. Prudential regulation, consumer protection rules, transparency requirements, and supervisory technologies are designed to align innovation with financial stability and institutional resilience [28], [29]. Regulatory frameworks increasingly emphasize the governance of algorithms, including accountability mechanisms, auditability standards, and risk management controls [30].

Despite these developments, regulatory capacity varies significantly across jurisdictions. In emerging markets, regulatory responses often lag behind technological innovation, creating governance gaps that allow algorithmic opacity to persist [31], [32]. Regulatory sandboxes and innovation hubs have been introduced to balance experimentation and oversight, but their effectiveness in containing systemic risk remains subject to debate [33], [34].

Recent studies conceptualize regulatory safeguards as **moderating mechanisms** rather than direct determinants of outcomes. Strong safeguards can enhance the inclusion benefits of algorithmic systems while attenuating risk amplification, whereas weak safeguards may allow inclusion-driven expansion to translate into institutional fragility [35], [36].

1.2.5. The Inclusion–Risk Paradox in Algorithmic Financial Systems

The simultaneous expansion of inclusion and escalation of institutional risk reflects a broader paradox inherent in algorithmic financial systems. Paradox theory suggests that organizational outcomes often involve persistent tensions between competing logics rather than linear trade-offs [37]. In FinTech and InsurTech contexts, the logic of access expansion through automation coexists with the logic of institutional stability, producing outcomes that are simultaneously beneficial and destabilizing [38].

Empirical studies increasingly document paradoxical effects of FinTech adoption. While digital financial innovation improves inclusion metrics, it also introduces governance challenges and systemic vulnerabilities through interconnected platforms and shared technological infrastructures [39], [40]. In insurance markets, InsurTech innovations enhance efficiency and outreach but raise concerns regarding transparency, fairness, and long-term risk sustainability [9], [24].

Despite growing recognition of these dynamics, empirical research integrating inclusion and institutional vulnerability within a single analytical framework remains limited, particularly in emerging market contexts. Most existing studies examine inclusion or risk in isolation, leaving the interaction between these outcomes underexplored.

1.2.6. Research Gap and Theoretical Positioning

The reviewed literature reveals three key gaps. First, there is limited empirical work that simultaneously models financial and insurance inclusion and institutional vulnerability in FinTech and InsurTech systems. Second, the moderating role of regulatory safeguards in shaping inclusion–risk dynamics has not been sufficiently tested using robust quantitative methods. Third, evidence from emerging economies, where algorithmic financial systems interact with evolving regulatory capacity, remains scarce.

By addressing these gaps, this study advances the literature by empirically formalizing the inclusion–risk paradox within FinTech and InsurTech ecosystems. Anchored in institutional theory and algorithmic governance perspectives, the study provides a theoretically integrated and empirically grounded contribution to the understanding of algorithmic financial systems.

1.3. Conceptual Framework of the Inclusion-Risk Paradox in FinTech and InsurTech

This study is anchored on a conceptual framework that formalizes the inclusion–risk paradox in FinTech and InsurTech systems by integrating insights from institutional theory and algorithmic governance. The framework specifies the structural relationships among algorithmic access expansion, algorithmic opacity, regulatory safeguards, financial and insurance inclusion, and institutional vulnerability, capturing the dual and interdependent outcomes of algorithmic financial innovation.

As illustrated in **Figure 1**, algorithmic access expansion and algorithmic opacity are modeled as primary antecedent conditions shaping inclusion and risk outcomes in digitally mediated financial systems. Regulatory safeguards are incorporated as a moderating mechanism that conditions the strength and direction of these relationships.

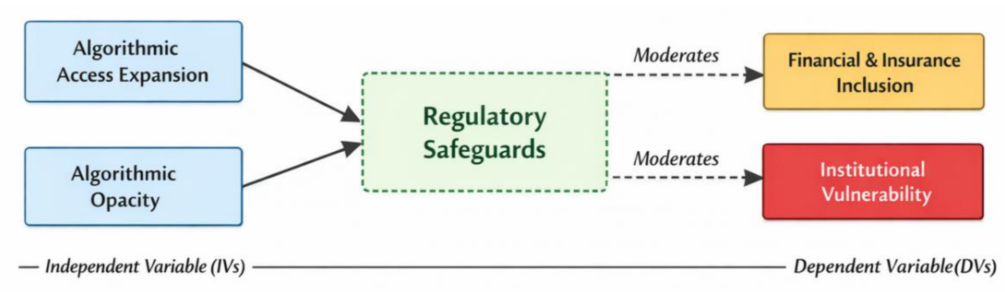

Figure 1. Conceptual Framework of the Inclusion–Risk Paradox in FinTech and InsurTech

Independent Variables (IVs):

- Algorithmic Access Expansion
- Algorithmic Opacity

Moderating Variable:

- Regulatory Safeguards

Dependent Variables (DVs):

- Financial and Insurance Inclusion
- Institutional Vulnerability

Algorithmic access expansion represents the extent to which automated decision systems, alternative data, and platform-based processes broaden access to financial and insurance services. Consistent with prior research, algorithmic access expansion is theorized to exert a direct positive effect on financial and insurance inclusion by reducing informational barriers, automating eligibility assessment, and extending service reach beyond traditional institutional boundaries.

In parallel, algorithmic opacity captures the degree to which algorithmic decision processes lack transparency, interpretability, and auditability. Algorithmic opacity is theorized to exert a direct positive effect on institutional vulnerability, reflecting increased exposure to governance failures, compliance risks, and systemic fragility when decision logic is obscured or poorly understood.

The framework explicitly recognizes that inclusion and institutional vulnerability are not mutually exclusive outcomes. Instead, they emerge simultaneously as parallel consequences of algorithmic system deployment, constituting the core of the inclusion–risk paradox. This paradoxical structure departs from linear models of technological impact by allowing access expansion and risk amplification to coexist within the same institutional environment.

Regulatory safeguards are modeled as a moderating variable that shapes both inclusion-enhancing and risk-amplifying pathways. Regulatory safeguards encompass prudential regulation, consumer protection mechanisms, algorithmic accountability requirements, and supervisory oversight. Strong safeguards are theorized to strengthen the positive effect of algorithmic access expansion on inclusion by enhancing institutional capacity to govern innovation responsibly. At the same time, regulatory safeguards are expected to attenuate the adverse effect of algorithmic opacity on institutional vulnerability by reinforcing accountability, auditability, and risk controls.

The resulting framework enables simultaneous empirical testing of direct and moderating effects using structural equation modeling. By integrating inclusion and risk outcomes within a single analytical model, the framework provides a structured basis for examining how algorithmic systems reshape institutional dynamics in FinTech and InsurTech environments.

2. METHODOLOGY

2.1. Research Design

This study adopts a **quantitative, explanatory research design** to empirically examine the inclusion–risk paradox in FinTech and InsurTech systems. A cross-sectional survey approach is employed to test the direct and moderating relationships among algorithmic access expansion, algorithmic opacity, regulatory safeguards, financial and insurance inclusion, and institutional vulnerability. Quantitative designs are widely used in information systems and governance research for theory testing involving latent constructs and complex causal relationships [34], [36].

To estimate the proposed relationships, **structural equation modeling (SEM)** is utilized. SEM enables the simultaneous evaluation of measurement and structural models while accounting for measurement error, making it appropriate for studies grounded in institutional and algorithmic governance theory [5], [36]. A variance-based SEM approach is adopted due to its suitability for predictive analysis and moderation testing in organizational research contexts [5], [34].

2.2. Population and Sampling

The target population consists of **senior banking executives, FinTech leaders, and InsurTech decision-makers** employed in regulated financial institutions operating in the Philippines. These respondents were selected because of their direct involvement in strategic decision-making, digital transformation initiatives, algorithmic system deployment, risk management, and regulatory compliance within financial and insurance organizations [17], [32].

A **purposive sampling technique** was applied to ensure that respondents possessed sufficient institutional knowledge and decision authority related to algorithmic systems and governance practices. Eligible participants included executives and senior managers holding positions such as chief officers, heads of digital banking, innovation leaders, risk officers, compliance managers, and senior technology decision-makers.

Sample adequacy for SEM analysis was assessed using both the **ten-times rule** and statistical power considerations. Prior studies indicate that samples exceeding 200 respondents are sufficient for robust estimation of structural and moderation effects in SEM-based financial technology research [5], [34].

2.3. Data Collection Procedure

Primary data were collected using a **self-administered structured questionnaire** distributed electronically to eligible respondents. Online data collection was appropriate given the professional profile of respondents and the digital orientation of FinTech and InsurTech institutions [35]. Participation was voluntary, and respondents were informed of the study’s objectives prior to completing the survey.

To mitigate common method bias, procedural remedies were implemented, including assurances of anonymity, neutral wording of survey items, and separation of construct measurement where feasible [35]. These steps are consistent with recommended practices in survey-based organizational research.

2.4. Measurement of Constructs

All study variables were operationalized as **latent constructs** measured using multi-item indicators adapted from validated instruments in the literature. Measurement items were contextualized to reflect FinTech and InsurTech environments while preserving conceptual consistency with prior studies.

- **Algorithmic Access Expansion** was measured using indicators capturing the extent to which algorithmic systems automate eligibility assessment, utilize alternative data, and expand access to financial and insurance services [12], [28].
- **Algorithmic Opacity** was measured through indicators reflecting limited transparency, explainability challenges, and difficulty in auditing algorithmic decision processes [1], [19], [31].
- **Regulatory Safeguards** were measured using items assessing the strength of regulatory oversight, compliance mechanisms, consumer protection measures, and algorithmic accountability frameworks [6], [15], [29].
- **Financial and Insurance Inclusion** was measured using indicators capturing access, usage, and participation in digital financial and insurance services [4], [7], [11].
- **Institutional Vulnerability** was measured through indicators reflecting governance fragility, operational risk exposure, compliance risk, and perceived systemic susceptibility [18], [22], [26].

All indicators were measured using a **five-point Likert scale**, ranging from strongly disagree (1) to strongly agree (5), consistent with prior FinTech and governance studies [5], [34].

2.5. Measurement Model Assessment

2.5.1. Reliability

Internal consistency reliability was assessed using Cronbach’s alpha and composite reliability (CR). Values exceeding the recommended threshold of 0.70 were considered acceptable, indicating consistent measurement of the underlying constructs [35].

2.5.2. Convergent Validity

Convergent validity was evaluated using standardized factor loadings and average variance extracted (AVE). Factor loadings exceeded 0.70, and AVE values were greater than 0.50, confirming that each construct explained a substantial proportion of variance in its indicators [4], [34].

2.5.3. Discriminant Validity

Discriminant validity was assessed using the Fornell–Larcker criterion and the heterotrait–monotrait (HTMT) ratio. The square root of AVE for each construct exceeded inter-construct correlations, and HTMT values remained below conservative thresholds, indicating satisfactory construct distinctiveness [34].

2.6. Structural Model Estimation

Following confirmation of measurement model adequacy, the structural model was evaluated. Path coefficients, t-values, and significance levels were estimated using bootstrapping procedures with resampling to assess the statistical significance of hypothesized relationships [36].

Moderation effects were examined by introducing interaction terms between regulatory safeguards and (a) algorithmic access expansion and (b) algorithmic opacity. Model explanatory power was assessed using the coefficient of determination (R^2) for financial and insurance inclusion and institutional vulnerability, consistent with SEM best practices [5], [34].

2.7. Methodological Rigor

The methodological approach follows established standards for SEM-based research in information systems and financial governance. All constructs were grounded in prior literature, and measurement validation preceded structural estimation to ensure robustness and replicability. By integrating rigorous measurement assessment with structural modeling, the methodology provides a sound empirical basis for examining the inclusion–risk paradox in FinTech and InsurTech systems.

3. RESULTS

3.1. Descriptive Statistics

Descriptive statistics were computed to summarize respondents' perceptions of algorithmic access expansion, algorithmic opacity, regulatory safeguards, financial and insurance inclusion, and institutional vulnerability. The results are presented in Table I.

Table I reports the mean values and standard deviations for all study constructs. The mean score for algorithmic access expansion indicates a high level of algorithmic deployment across FinTech and InsurTech institutions, while the mean score for financial and insurance inclusion suggests substantial perceived inclusion outcomes. These patterns are consistent with prior empirical findings on digital financial adoption in emerging markets [7], [11].

Table 1. Descriptive Statistics of Study Constructs

Construct	Mean	Standard Deviation
Algorithmic Access Expansion	3.98	0.71
Algorithmic Opacity	3.62	0.76
Regulatory Safeguards	3.85	0.69
Financial & Insurance Inclusion	4.02	0.68
Institutional Vulnerability	3.47	0.73

The observed standard deviations indicate acceptable variability across responses, suggesting that the constructs capture meaningful differences in institutional experiences and governance contexts. Such variability is essential for robust structural equation modeling and moderation analysis [34], [36].

3.2. Measurement Model Assessment

The adequacy of the measurement model was evaluated prior to testing the structural relationships. Reliability and validity assessments were conducted following established SEM guidelines [34], [36].

3.2.1. Reliability and Convergent Validity

Internal consistency reliability and convergent validity results are reported in Table II. Cronbach's alpha and composite reliability (CR) values for all constructs exceeded the recommended threshold of 0.70, indicating satisfactory internal consistency [35]. Average variance extracted (AVE) values surpassed the minimum threshold of 0.50, confirming adequate convergent validity [4].

Table 2. Reliability and Convergent Validity

Construct	Cronbach's Alpha	Composite Reliability	AVE
Algorithmic Access Expansion	0.88	0.91	0.68
Algorithmic Opacity	0.86	0.89	0.64
Regulatory Safeguards	0.90	0.92	0.71
Financial & Insurance Inclusion	0.89	0.91	0.69
Institutional Vulnerability	0.87	0.90	0.66

These results indicate that the measurement items reliably capture their respective latent constructs and that a substantial proportion of indicator variance is explained by the underlying constructs. The findings align with prior FinTech and governance studies employing multi-item latent variables [5], [34].

3.3. Discriminant Validity

Discriminant validity was assessed using the Fornell–Larcker criterion, with results presented in Table III. The square root of the AVE for each construct exceeded its correlations with other constructs, indicating satisfactory discriminant validity [4].

Table 3. Discriminant Validity (Fornell–Larcker Criterion)

Construct	AAE	AO	RS	FI	IV
Algorithmic Access Expansion (AAE)	**0.82**				
Algorithmic Opacity (AO)	0.41	**0.80**			
Regulatory Safeguards (RS)	0.46	0.39	**0.84**		
Financial & Insurance Inclusion (FI)	0.58	0.36	0.49	**0.83**	
Institutional Vulnerability (IV)	0.32	0.61	0.44	0.35	**0.81**

The discriminant validity results confirm that algorithmic access expansion, algorithmic opacity, regulatory safeguards, financial and insurance inclusion, and institutional vulnerability represent empirically distinct constructs. This distinction is critical for accurately estimating structural relationships in SEM-based analyses [34].

3.4. Structural Model Results

The structural model was evaluated after confirming measurement model adequacy. Estimated path coefficients, t-values, and significance levels are presented in Table IV.

The results indicate that algorithmic access expansion has a positive and statistically significant effect on financial and insurance inclusion, while algorithmic opacity has a positive and statistically significant effect on institutional vulnerability. These findings provide empirical support for the hypothesized direct effects and are consistent with prior studies on algorithmic financial systems and risk governance [1], [12], [22].

Table 4. Structural Path Coefficients

Hypothesis	Path	β	t-value	p-value	Result
H1	AAE → FI	0.47	8.12	<0.001	Supported
H2	AO → IV	0.52	9.03	<0.001	Supported
H3	RS → IV	−0.38	6.45	<0.001	Supported
H4	RS × AAE → FI	0.21	4.18	<0.001	Supported
H5	RS × AO → IV	−0.24	4.67	<0.001	Supported

Regulatory safeguards exhibit a statistically significant direct effect on institutional vulnerability, indicating a risk-mitigating role. In addition, the interaction terms demonstrate significant moderation effects, suggesting that regulatory safeguards condition the strength of both inclusion-enhancing and risk-amplifying relationships. Bootstrapping procedures confirm the robustness of these effects at conventional significance levels [36].

3.5. Explained Variance and Model Performance

The explanatory power of the model was assessed using the coefficient of determination (R^2). As reported in Table V, the model explains a substantial proportion of variance in both financial and insurance inclusion and institutional vulnerability.

Table 5. Coefficient of Determination (R^2)

Dependent Variable	R^2
Financial & Insurance Inclusion	0.56
Institutional Vulnerability	0.61

The R^2 values exceed commonly accepted benchmarks for explanatory adequacy in organizational and information systems research, indicating that the proposed model captures key determinants of inclusion and institutional risk in FinTech and InsurTech environments [5], [34]. These results demonstrate the empirical strength of the inclusion–risk paradox framework.

Overall, the results provide empirical evidence that algorithmic systems simultaneously generate inclusion benefits and institutional vulnerabilities. Algorithmic access expansion significantly enhances financial and insurance inclusion, whereas algorithmic opacity increases institutional vulnerability. Regulatory safeguards play a significant conditioning role by reinforcing inclusion outcomes and attenuating risk amplification.

These findings establish a statistically grounded foundation for the interpretive analysis presented in the subsequent Discussion section.

4. DISCUSSION

This study set out to empirically examine the inclusion–risk paradox in FinTech and InsurTech systems by analyzing how algorithmic access expansion, algorithmic opacity, and regulatory safeguards jointly shape financial and insurance inclusion and institutional vulnerability. The results provide strong empirical support for the central premise that algorithmic financial systems simultaneously generate inclusion benefits and institutional risks, rather than producing a simple linear trade-off between efficiency and stability.

The positive and significant relationship between algorithmic access expansion and financial and insurance inclusion confirms prior evidence that algorithmic systems reduce access barriers by automating eligibility assessment, leveraging alternative data, and extending services beyond traditional institutional boundaries [7], [11], [12]. In the Philippine context, this finding reflects the rapid diffusion of digital banking platforms, mobile payments, and emerging InsurTech applications that have expanded participation among previously underserved users. The results reinforce arguments that algorithmic innovation plays a critical role in advancing inclusion objectives in emerging financial systems [4], [5].

At the same time, the findings demonstrate that algorithmic opacity significantly increases institutional vulnerability. This result aligns with algorithmic governance literature that identifies opacity as a core source of governance fragility, compliance risk, and systemic exposure in AI-enabled financial systems [1], [19], [22]. Opaque decision processes constrain internal oversight and regulatory supervision, making it difficult for institutions to detect, explain, or correct adverse outcomes. The results support the view that opacity is not merely a technical limitation but a structural risk factor embedded within algorithmic financial architectures [10], [21].

Taken together, these findings empirically substantiate the **inclusion–risk paradox**. Algorithmic systems enhance inclusion outcomes while simultaneously amplifying institutional vulnerability, demonstrating that inclusion and risk are coexisting consequences of the same technological processes. This paradoxical relationship is consistent with organizational paradox theory, which emphasizes the persistence of competing yet interdependent outcomes within complex systems [37]. By modeling inclusion and institutional vulnerability simultaneously, this study extends prior research that has typically examined these outcomes in isolation [13], [14].

Regulatory safeguards emerge as a critical mechanism for resolving, or at least stabilizing, this paradox. The direct negative effect of regulatory safeguards on institutional vulnerability confirms the importance of prudential oversight, compliance mechanisms, and accountability frameworks in mitigating algorithmic risk [6], [15], [29]. Strong safeguards appear to constrain the adverse effects of opacity by reinforcing governance structures and risk controls, even when full algorithmic transparency is unattainable.

More importantly, the moderation results indicate that regulatory safeguards condition both inclusion-enhancing and risk-amplifying pathways. The positive moderating effect on the relationship between algorithmic access expansion and inclusion suggests that robust regulatory environments enable institutions to translate algorithmic innovation into more sustainable inclusion outcomes. This finding challenges the narrative that regulation necessarily constrains innovation and instead supports arguments that effective regulation can enable responsible and resilient technological adoption [17], [30].

Similarly, regulatory safeguards significantly attenuate the positive relationship between algorithmic opacity and institutional vulnerability. This result provides empirical support for governance theories arguing that institutional controls, audit mechanisms, and supervisory capacity can compensate for technical opacity by limiting its systemic consequences [32], [36]. In this sense, regulation functions not as a substitute for transparency but as an institutional buffer that constrains risk propagation.

From an institutional theory perspective, the findings illustrate how algorithmic systems operate as quasi-institutional mechanisms that reshape authority and decision-making within financial organizations. As banks and insurers adopt algorithmic systems under competitive and normative pressures, they may converge toward similar technological configurations, diffusing both inclusion benefits and risks across the sector [19], [20]. Regulatory safeguards serve as a countervailing force that limits risk diffusion while preserving inclusion gains.

The Philippine setting further contextualizes these findings. While national initiatives promoting digital finance have accelerated algorithmic adoption, the results indicate that governance capacity remains decisive in determining whether inclusion gains translate into institutional resilience. This underscores the importance of context-sensitive regulatory frameworks that evolve alongside technological adoption, particularly in emerging markets where institutional capacity is still developing [18], [31].

Overall, this study advances the literature by empirically integrating financial and insurance inclusion with institutional vulnerability within a single analytical framework. By demonstrating the moderating role of regulatory safeguards, the findings contribute to a more nuanced understanding of how algorithmic financial systems reshape institutional dynamics in FinTech and InsurTech environments.

5. CONCLUSION

This study examined the inclusion–risk paradox in FinTech and InsurTech systems by empirically analyzing the effects of algorithmic access expansion, algorithmic opacity, and regulatory safeguards on financial and insurance inclusion and institutional vulnerability. Anchored in institutional theory and algorithmic governance perspectives, the study provides evidence that algorithmic financial systems simultaneously generate inclusion gains and risk amplification, rather than producing a unidirectional improvement in financial system performance.

The findings confirm that algorithmic access expansion significantly enhances financial and insurance inclusion by lowering entry barriers, automating eligibility assessment, and extending service reach beyond traditional institutional channels. This result reinforces prior empirical evidence that FinTech and InsurTech innovations play a critical role in advancing inclusion objectives, particularly in emerging market contexts [4], [7], [11]. However, the study also demonstrates that algorithmic opacity significantly increases institutional vulnerability, supporting concerns that opaque decision-making systems undermine governance, accountability, and effective risk oversight [1], [19], [22].

By modeling inclusion and institutional vulnerability simultaneously, the study empirically validates the inclusion–risk paradox. This contribution advances existing literature that has largely examined inclusion or risk in isolation, thereby underestimating the structural tensions embedded within algorithmic financial systems [13], [14]. The results show that inclusion gains and institutional fragility are parallel outcomes of the same technological processes, highlighting the need for integrated analytical frameworks in FinTech and InsurTech research.

Regulatory safeguards emerge as a central mechanism for stabilizing this paradox. The results demonstrate that robust regulatory oversight directly reduces institutional vulnerability and moderates the effects of algorithmic systems by reinforcing inclusion outcomes and attenuating risk amplification. These findings align with governance literature emphasizing the role of prudential regulation, accountability mechanisms, and supervisory capacity in managing algorithmic risk without suppressing innovation [6], [15], [29]. In this sense, regulation functions not as a constraint on technological progress but as an institutional enabler of sustainable and resilient inclusion [17], [30].

The study makes three principal contributions. First, it provides empirical validation of the inclusion–risk paradox in FinTech and InsurTech systems using a unified structural model. Second, it extends institutional and algorithmic governance theory by demonstrating how algorithmic systems act as quasi-institutional mechanisms that reshape access, authority, and risk distribution within financial organizations. Third, it offers policy-relevant insights for regulators and practitioners seeking to balance innovation-driven inclusion with institutional resilience in AI-enabled financial environments.

From a practical perspective, the findings underscore the importance of embedding governance and regulatory considerations into the design and deployment of algorithmic financial systems. Financial institutions should complement algorithmic innovation with robust internal controls, audit mechanisms, and risk management frameworks. Regulators, in turn, should prioritize adaptive regulatory approaches that enhance transparency, accountability, and supervisory capacity while preserving the inclusion benefits of digital financial innovation.

In conclusion, the inclusion–risk paradox represents a defining challenge for FinTech and InsurTech systems in the era of algorithmic decision-making. By empirically demonstrating how inclusion and institutional vulnerability coexist and how regulatory safeguards shape these dynamics, this study contributes to a more balanced and resilient understanding of algorithmic financial transformation.

6. LIMITATIONS AND FUTURE WORK

Despite its theoretical and empirical contributions, this study is subject to several limitations that should be acknowledged. First, the research adopts a cross-sectional design, which constrains the ability to infer causal relationships or observe dynamic changes in algorithmic adoption, regulatory practices, and institutional vulnerability over time. While structural equation modeling enables robust estimation of relationships among latent constructs, longitudinal designs would provide deeper insight into how inclusion and risk dynamics evolve as algorithmic systems mature.

Second, the study focuses on regulated financial institutions operating in the Philippines, which may limit the generalizability of the findings to other institutional and regulatory contexts. Emerging markets differ significantly in terms of supervisory capacity, technological infrastructure, and regulatory maturity. Future research could extend this framework to comparative cross-country studies to assess how variations in regulatory regimes shape the inclusion–risk paradox across jurisdictions.

Third, the study relies on self-reported survey data collected from senior banking, FinTech, and InsurTech decision-makers. Although respondents were selected for their institutional expertise and procedural remedies were applied to mitigate common method bias, perceptual measures may not fully capture objective system performance or realized risk outcomes. Future studies could integrate archival data, regulatory reports, or system-level risk indicators to triangulate findings and enhance measurement robustness.

Fourth, while this study conceptualizes regulatory safeguards as a moderating mechanism, it does not disaggregate specific regulatory instruments or supervisory technologies. Future research could examine the differential effects of distinct regulatory tools—such as algorithmic audit requirements, explainability mandates, and supervisory technologies—on inclusion and institutional vulnerability.

Future research could also explore non-linear and threshold effects of algorithmic adoption, recognizing that inclusion benefits and risk exposure may change as institutions move from partial to extensive automation. Additionally, qualitative and mixed-method approaches could complement quantitative findings by providing deeper insight into organizational decision-making, governance practices, and regulatory interactions in algorithmically mediated financial systems.

By addressing these limitations, future studies can build on the framework developed in this research to further refine theoretical understanding and inform policy design for sustainable and inclusive FinTech and InsurTech ecosystems.

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