Does Broader Insurance Weaken Preventive Supply Chain Resilience? Moral Hazard, Verification, and the Limits of Visibility

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Does Broader Insurance Weaken Preventive Supply Chain Resilience? Moral Hazard, Verification, and the Limits of Visibility

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Abstract

This study examines whether broader supply chain insurance coverage is associated with lower preventive resilience investment through perceived managerial moral hazard. Drawing on moral hazard theory and supply chain resilience research, it tests a moderated-mediation model using survey data from 241 managers in manufacturing-intensive firms. PLS-SEM is used as the main estimator, and covariance-based SEM is reported as an estimator-sensitivity check. Results show that insurance coverage breadth is positively associated with moral hazard perceptions, moral hazard perceptions are negatively associated with preventive resilience investment, and preventive investment is negatively associated with perceived disruption impact. Moral hazard perceptions significantly mediate the coverage breadth–preventive investment relationship, while the direct effect is not significant. The total effect of insurance coverage breadth on preventive resilience investment is negative and significant. Firm-perceived insurer verification stringency is associated with a weaker coverage–moral hazard perception relationship, whereas supply chain visibility provides a smaller attenuation effect. Exploratory risk-type moderation is directional but inconclusive. This study offers evidence from an emerging-market manufacturing context and suggests that contractual verification may help preserve prevention incentives, without estimating causal treatment effects.

Keywords: supply chain insurance; moral hazard; preventive resilience; business interruption; PLS-SEM; CB-SEM; verification stringency

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1. Introduction

Supply chain disruption insurance is widely promoted as a cornerstone of corporate resilience. Following the 2011 Great East Japan Earthquake and tsunami, the 2017 NotPetya cyberattack, the COVID-19 pandemic, and recent Persian Gulf and Red Sea shipping disruptions, demand for different supply-chain-related insurance coverages such as business interruption, contingent business interruption, cyber, and trade-credit coverage has expanded sharply (Marsh 2024; Chandio et al. 2026), with insurers responding through broader products and higher capacity following such crises (Aon 2024;

Abdelhedi and Ben Hamida 2026). Yet a basic tension underlies this expansion: insurance and prevention may function as partial substitutes in managerial decision-making, so broader coverage may be associated with lower perceived urgency to maintain preventive resilience investments. Whether broader supply chain insurance is associated with lower preventive resilience investment, and through which managerial perceptions, is therefore, an important question for operations and risk-management research (Wieland et al. 2023).

Moral hazard theory predicts that risk transfer reduces the marginal incentive to invest in prevention (Bağcı and Küçükbayrak 2026). In supply chain settings, however, the relationship is more complex than in personal or property insurance. Resilience investments often have option-value rather than continuous returns; verification of preventive effort is unusually difficult because much of supply chain resilience is relational rather than physical (Pettit et al. 2019); and risk profiles vary across firms, with some risks being preventable through internal effort and others being systemic and largely uncontrollable (Busse et al. 2025). Whether and when insurance coverage breadth diminishes preventive investment is, therefore, an empirical question with both theoretical and managerial relevance, especially as insurers explore parametric and visibility-linked products that more tightly couple coverage to observable firm behaviour (Lücker et al. 2025).

This study addresses three research questions within its empirical setting. First, is insurance coverage breadth associated with lower preventive resilience investment through perceived managerial moral hazard? Second, are supply chain visibility and insurer verification stringency associated with a weaker coverage–moral hazard relationship? Third, does the pattern differ descriptively across firms whose dominant risks are more preventable rather than systemic? These questions are examined using cross-sectional survey data from 241 managers in Iranian manufacturing-intensive firms. The evidence is, therefore, interpreted as context-bound associational evidence, not as a universal test of moral hazard across all insurance markets.

This study's context, Iran, is used as a theoretically relevant emerging-market setting in which manufacturing firms face considerable supply chain disruption exposure, while supply chain insurance, insurer verification, and preventive resilience practices vary across firms. This variation makes the setting useful for examining whether perceived insurance protection and perceived verification are associated with prevention incentives. This study therefore tests whether a theoretically predicted mechanism is observable in this setting, while leaving cross-country generalisation to future comparative research.

This study makes three contributions. First, we move moral hazard in supply chain insurance from theoretical conjecture toward empirical operationalisation by developing an initial four-item perceptual scale that captures managers' perceived reduction in prevention urgency under insurance coverage. However, as this is not a behavioural loss-event measure, it requires further validation in independent samples. Second, this study compares two theoretically distinct attenuation mechanisms, firm-side visibility and firm-perceived insurer verification, and finds that perceived verification shows a stronger and more consistent attenuation pattern than visibility. This finding challenges the prevailing "visibility-as-resilience" narrative in the supply chain literature (Brusset 2016; Zheng and Brintrup 2025) and points toward an incentive-design view consistent with principal–agent theory and recent evidence from analogous contexts such as telematics-based auto insurance (Holzapfel et al. 2024). Third, this study explores risk type as an exploratory condition, assessing descriptively whether the moral hazard perception pattern differs when firms' dominant supply chain risks are more preventable rather than systemic.

2. Theoretical Background and Hypotheses

2.1. Insurance, Moral Hazard, and Supply Chain Risk

Moral hazard—the tendency of insured parties to reduce loss-prevention effort because the financial consequences of loss are partially externalized to the insurer—is a foundational concept in insurance economics (Bağcı and Küçükbayrak 2026). The mechanism arises when the insurer cannot perfectly observe or contract on the insured's preventive behaviour (Shavell 1979). Empirical evidence of moral hazard has been documented in health insurance (Zhou et al. 2025), automobile insurance (Ashayeri et al. 2025), crop insurance (Bhattarai et al. 2026), and cyber insurance (Dou et al. 2020).

Empirical applications of moral hazard theory to firm-level operational risk remain limited, particularly in supply chain contexts where insurance coverage may shape managerial perceptions of preventive resilience investment. Bode et al. (2011) examine organisational responses to supply chain disruptions, but do not measure insurance-induced behavioural responses. Wakolbinger and Cruz (2011) model risk-management contracts in supply chains theoretically, highlighting the relevance of contractual arrangements for managing disruption risk. More recent supply chain resilience research has called for stronger empirical operationalisation of behavioural mechanisms in disruption and resilience contexts (Wieland et al. 2023). Accordingly, empirical supply chain research has given limited attention to managerial moral hazard as a perceptual mechanism linking insurance coverage to preventive resilience investment.

In supply chain contexts, three features sharpen the moral hazard problem. First, much resilience is relational (e.g., qualified backup suppliers, contingency contracts) rather than physical, making it harder for insurers to verify (Pettit et al. 2019). Second, the benefits of resilience often accrue to other actors in the chain, generating positive externalities that firms do not fully internalize, even absent insurance (Wakolbinger and Cruz 2011). Third, disruption losses are heavy-tailed, so insurance and prevention interact under deep uncertainty (Guo et al. 2025). Drawing on these arguments, broader insurance coverage is expected to be associated with stronger managerial moral hazard perceptions. Accordingly, the first hypothesis is articulated as follows:

H1. *Insurance coverage breadth is positively associated with moral hazard perceptions.*

Moral hazard perceptions should also be associated with preventive resilience investment because many resilience actions require discretionary managerial attention, upfront expenditure, and organisational commitment before any disruption occurs. Measures such as backup suppliers, safety stock, supplier qualification, geographic diversification, and early-warning systems impose immediate costs, while their benefits are uncertain and often realised only during rare disruption events (Guo et al. 2025). When managers perceive insurance coverage as absorbing a substantial portion of disruption-related losses, the perceived marginal benefit of such preventive investment may decline. In this sense, insurance can become a behavioural substitute for prevention, not because coverage eliminates operational risk, but because it reduces the urgency of investing in costly ex ante safeguards (Dou et al. 2020). This logic is consistent with classical moral hazard theory, which predicts lower preventive effort when insured actors are partially protected from loss consequences (Shavell 1979), and with recent evidence from other insurance contexts showing that coverage may weaken self-protection incentives (Bağcı and Küçükbayrak 2026). Accordingly, the following hypothesis is proposed:

H2. *Moral hazard perceptions are negatively associated with preventive supply chain resilience investment.*

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2.2. Preventive Resilience Investment and Disruption Impact

Supply chain resilience refers to a firm's ability to anticipate, absorb, respond to, and recover from disruptions (Seif and Jafari 2026). Preventive resilience investment encompasses ex ante actions that reduce disruption probability or severity, including dual sourcing, safety stock, supplier qualification, and risk monitoring (Ambulkar et al. 2014). Empirical work consistently finds that such investments mitigate disruption impact (Mohsendokht et al. 2026; Wagner and Bode 2008). Accordingly, firms that invest more systematically in preventive resilience should be better positioned to reduce the severity of disruption consequences, which leads to the formulation of the third hypothesis:

H3. *Preventive supply chain resilience investment is negatively associated with perceived disruption impact.*

Combining H1 and H2 suggests that insurance coverage breadth may be associated with preventive resilience investment indirectly through moral hazard perceptions. If broader coverage increases the perception that disruption-related losses are externally absorbed, managers may feel less urgency to maintain costly preventive safeguards. H3 then extends this logic downstream by linking preventive investment to perceived disruption impact. However, the focal mediation in this study concerns the more immediate behavioural pathway from insurance coverage breadth to preventive resilience investment through moral hazard perceptions. Based on this reasoning, the fourth hypothesis is formulated as follows:

H4. *Moral hazard perceptions mediate the relationship between insurance coverage breadth and preventive resilience investment.*

2.3. Boundary Conditions: Visibility, Verification, and Risk Type

Although moral hazard is a robust theoretical prediction, classical insurance theory also identifies mechanisms that attenuate it: monitoring (which reduces information asymmetry), contractual verification (which conditions coverage on observable behaviour), and the nature of the underlying risk (Holmström 1979; Shavell 1979). We translate each into the supply chain setting, drawing on emerging InsurTech literature that has begun to formalize these mechanisms in operational risk markets (Cappiello 2020; Skryl and Hlushko 2023).

2.3.1. Supply Chain Visibility and Verification Stringency

Supply chain visibility is the firm's capacity to monitor suppliers, inventory, and disruption signals across its network (AlMahri et al. 2026; Wei and Wang 2010). Higher visibility reduces information asymmetries within the firm and may reduce managerial reliance on insurance as a substitute for active risk management. Recent work has linked visibility to faster disruption response and lower performance volatility (Jiang et al. 2025). Therefore, it is expected that visibility weakens the coverage–moral hazard link, leading to the fifth hypothesis formulation as follows:

H5a. *Supply chain visibility is associated with a weaker positive relationship between insurance coverage breadth and moral hazard perceptions.*

Insurers can attenuate moral hazard by conditioning coverage on observable risk-management practices, such as audits, certifications (e.g., international standards, business continuity plans, supplier mapping, supplier risk assessments, and renewal reviews (Choi et al. 2024; Cummins and Trainar 2009). When the insurer–firm contract embeds such verification, the firm's incentive to substitute insurance for prevention is reduced because preventive effort affects coverage continuity, premium pricing, and renewal terms. This contractual logic parallels the role of telematics in automobile insurance, which has been shown to substantially reduce moral hazard among insured drivers (Holzapfel et al. 2024).

H5b. *Firm-perceived insurer verification stringency is associated with a weaker positive relationship between insurance coverage breadth and moral hazard perceptions.*

2.3.2. Risk Type as an Exploratory Boundary Condition

Moral hazard perceptions are likely to be more relevant when the dominant risks faced by a firm are more preventable through internal effort. For risks that are preventable through firm-level action, such as supplier qualification failures or cyber-hygiene lapses, insurance may create a stronger substitution incentive because managers can choose whether to maintain or reduce preventive safeguards. For systemic risks, such as pandemics, geopolitical shocks, or large-scale climate events, prevention is largely infeasible, so the moral hazard perception mechanism should be weaker (Cinti et al. 2025; Kunreuther 1996; Tang 2006). However, because risk type is captured through a simpler risk-allocation measure rather than the same type of multi-item scale used for the main reflective constructs, we treat it as an exploratory boundary condition. We therefore examine whether the insurance coverage breadth–moral hazard perception association is descriptively stronger when the firm's dominant risks are more preventable, but we do not frame this test as a confirmatory hypothesis.

Figure 1 presents the proposed moderated-mediation model. Insurance coverage breadth is expected to be associated with perceived disruption impact through the sequential pathway of moral hazard perceptions and preventive resilience investment. The coverage–moral hazard perception relationship is the focal point of moderation, with supply chain visibility and firm-perceived insurer verification stringency positioned as confirmatory boundary conditions. Risk type is included as an exploratory boundary condition. The dashed path represents the indirect effect of insurance coverage breadth on preventive resilience investment through moral hazard perceptions.

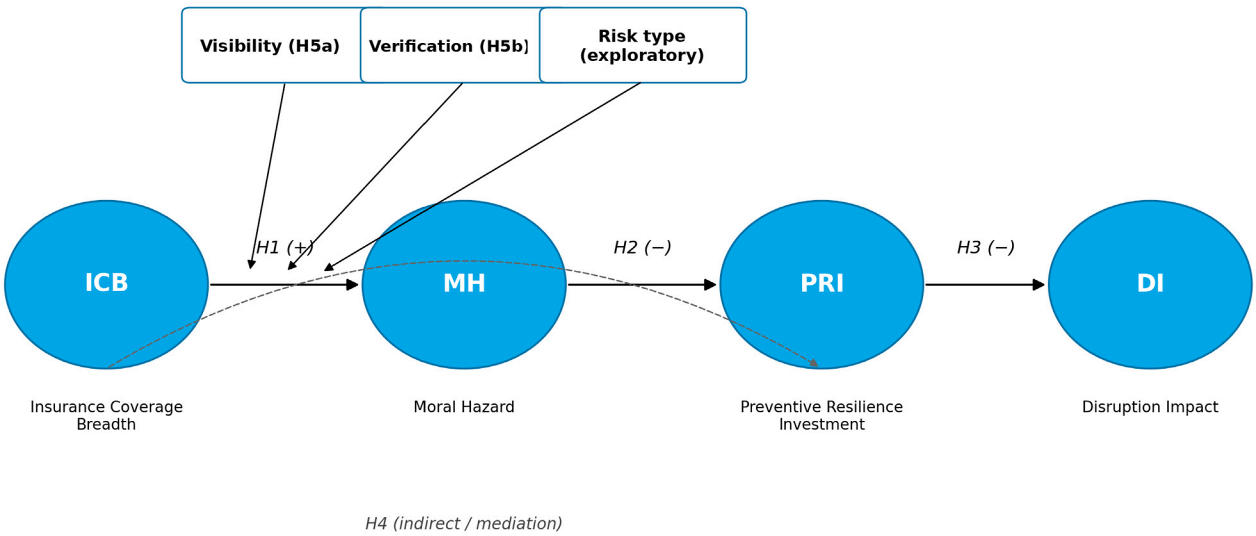

Figure 1. Proposed conceptual model.

3. Methods

3.1. Sample and Data Collection

Data were collected through an online cross-sectional survey of managers in Iranian manufacturing-intensive firms. Respondents were identified through the membership and affiliated-firm registry of the National Industrial Areas Association, and the survey was distributed between October 2025 and February 2026. Eligible respondents were those directly involved in supply chain, operations, procurement, risk or insurance decisions. Cases were retained only if the respondent's firm held at least one supply-chain-relevant insurance coverage and the respondent reported at least one year of relevant role tenure. The final analytical sample included 241 complete firm-level responses. The sample is, therefore, best described as insured manufacturing-intensive firms in Iran, not as all Iranian firms or global supply chains. Table 1 reports the industry and respondent role distribution.

Table 1. *Sample profile.*

Characteristic	Category	n	%
Industry	Automotive/Industrial equipment	65	27
	Chemicals/Pharmaceuticals	43	17.8
	Consumer goods manufacturing	77	32
	Other manufacturing	56	23.2
Total		241	100
Respondent role	Supply Chain Manager/Director	107	44.4
	Risk Manager/Insurance Manager	55	22.8
	Operations/COO	46	19.1
	Procurement Director	33	13.7
Total		241	100

3.2. Measurement

All multi-item constructs used seven-point Likert scales, ranging from 1 (strongly disagree) to 7 (strongly agree). Supply chain visibility was measured with five reflective items adapted from Brusset (2016) and Wei and Wang (2010), while perceived disruption impact was measured with five reflective recall-based items adapted from Wagner and Bode (2008) and Hendricks and Singhal (2005). These items capture managers' perceived operational, financial, and relational consequences of disruptions, not objective disruption-event frequency or audited loss distributions. Moral hazard perceptions were measured using four reflective items developed for this study based on moral hazard theory (Pauly 1968; Holmström 1979; Shavell 1979), with item development guided by MacKenzie et al. (2011). These items capture managers' perceived reduction in prevention urgency under insurance coverage; they do not directly measure observed behavioural moral hazard or post-loss prevention effort.

Insurance coverage breadth was operationalised as a seven-indicator formative composite developed for this study and informed by Cummins and Trainar (2009) and Marsh (2024). The construct captured business interruption coverage, contingent business interruption coverage, cyber coverage, trade credit coverage, marine cargo and logistics liability coverage, the breadth of covered supply chain disruption causes, and the adequacy of insurance limits. Because the construct is based on firm-reported coverage breadth and perceived adequacy of limits, it captures managerial perceptions of the scope and expected usefulness of coverage rather than verified insurer-side payout capacity. Firm-perceived insurer verification stringency was operationalised as a six-indicator formative composite developed for this study and informed by Choi et al. (2024) and Cummins and Trainar (2009). The indicators ask respondents whether their insurer requires audits, certifications, documented continuity plans, supplier mapping, supplier risk-assessment evidence, and review of risk-control measures before policy renewal. The construct therefore captures manager-reported perceptions of insurer verification requirements, not insurer-side underwriting records, audited contractual enforcement, claims-condition compliance, or premium-pricing rules. This distinction is particularly important in the Iranian emerging-market insurance setting, where verification practices may be less formalized than in mature OECD insurance markets. Preventive resilience investment was operationalised as a six-indicator formative composite adapted from Ambulkar et al. (2014), including backup suppliers, safety stock, alternate-supplier qualification, supplier-base geographic diversification, risk monitoring, and regular supply chain risk assessment and contingency-plan updating.

Risk type was measured using a constant-sum allocation in which respondents distributed 100 points between preventable and systemic risks; the standardized share of preventable risk served as the exploratory moderator (Tang 2006). Because this measure relies on a single allocation task rather than the multi-item reflective scales used for the focal constructs, risk type is treated as a simpler exploratory boundary-condition measure. A second confirmatory item was included to assess its convergent consistency, as reported in Section 4.1. To address common method bias ex ante, predictor and criterion items were separated in the questionnaire, filler items were used as buffers between blocks measuring insurance coverage and moral hazard, response anchors were varied, and anonymity was guaranteed (Podsakoff et al. 2024). Ex post, common method bias was assessed using full collinearity variance inflation factors and Harman's single-factor test (Almansour et al. 2025). Table 2 lists all reflective items, formative indicators and response anchors. This is particularly important because moral hazard perceptions, firm-perceived verification stringency, and perceived disruption impact are perceptual constructs rather than objective insurer-side or event-level measures.

Table 2. *Measurement items and construct operationalisations.*

Construct	Code	Item/Indicator
Insurance coverage breadth	ICB1	Our firm carries business interruption insurance with substantial coverage limits.
	ICB2	Our firm carries contingent business interruption insurance covering supplier disruptions.
	ICB3	Our firm carries cyber insurance covering supply chain and logistics systems.
	ICB4	Our firm carries trade credit insurance covering buyer or supplier default.
	ICB5	Our firm carries marine cargo and logistics liability insurance with broad terms.
	ICB6	Our firm's insurance policies cover a wide range of supply chain disruption causes.
	ICB7	Our firm's insurance limits would cover a substantial portion of losses from a major supply chain disruption.
Supply chain visibility	VIS1	We have real-time visibility into our suppliers' operations and capacity.
	VIS2	We can quickly identify disruptions occurring in our supply chain.
	VIS3	We have visibility into our tier-2 and tier-3 suppliers.
	VIS4	We can track inventory and shipments across our supply network.
	VIS5	We receive early warning signals of potential supply chain disruptions.

Table 2. *Cont.*

Construct	Code	Item/Indicator
Firm-perceived insurer verification stringency	VER1	Our insurer requires regular audits of our supply chain risk-management practices.
	VER2	Our insurer requires us to maintain certifications such as ISO 28000 or ISO 22301.
	VER3	Our insurer requires documented business continuity and contingency plans.
	VER4	Our insurer requires supplier mapping or supply chain visibility documentation.
	VER5	Our insurer requires evidence of supplier risk-assessment processes.
	VER6	Our insurer reviews and approves our risk-control measures before policy renewal.
Risk type	RT1	Please allocate 100 points across preventable risks and systemic risks to reflect the dominant supply chain risks your firm faces.
	RT2	Please indicate whether your firm's dominant supply chain risks are mainly systemic or mainly preventable.
Moral hazard	MH1	Our insurance coverage reduces the urgency of investing in supply chain disruption prevention.
	MH2	Insurance coverage reduces our need to invest in backup suppliers, redundancy, or alternative logistics arrangements.
	MH3	With insurance protection in place, extensive contingency planning becomes less critical.
	MH4	Our firm relies on insurance rather than internal resilience measures for some supply chain risks.
Preventive resilience investment	PRI1	Our firm maintains backup suppliers for critical inputs.
	PRI2	Our firm holds safety stock above operational minimum levels for critical components.
	PRI3	Our firm has formal qualification processes for alternate suppliers.
	PRI4	Our firm invests in geographic diversification of its supplier base.
	PRI5	Our firm invests in supply chain risk monitoring and early-warning systems.
	PRI6	Our firm conducts regular supply chain risk assessments and updates contingency plans.
Disruption impact	DI1	Supply chain disruptions have caused significant operational delays in our firm.
	DI2	Supply chain disruptions have caused substantial financial losses for our firm.
	DI3	Supply chain disruptions have damaged our customer relationships.
	DI4	Supply chain disruptions have required costly emergency measures to manage.
	DI5	The overall impact of supply chain disruptions on our firm has been severe.

Note. *All construct items were measured using a 7-point Likert scale ranging from 1 = strongly disagree to 7 = strongly agree, except RT1, which used a constant-sum allocation between preventable and systemic risks. RT2 was used as a confirmatory risk-type item for convergent-consistency assessment. VER indicators capture respondent-reported insurer requirements and should not be interpreted as insurer-side underwriting records or audited contractual enforcement.*

3.3. Analytical Approach

The structural model is estimated using partial least squares structural equation modelling (PLS-SEM). Aligned with the literature (Vafaei-Zadeh et al. 2025; Shojaei 2024), PLS-SEM was selected as the primary technique because (a) the model contains formative composites, (b) the research is exploratory in operationalising moral hazard perceptions in supply chain settings, and (c) the focus is on prediction-oriented theory development. Bootstrapping (5000 resamples, bias-corrected and accelerated confidence intervals) was used to assess path significance. Effect sizes (f^2), cross-validated predictive relevance (Q^2), and PLS-SEM fit indices (SRMR, NFI) were also computed (Hair et al. 2019). As an estimator-sensitivity check, the structural model is re-estimated using covariance-based SEM (CB-SEM) with maximum-likelihood estimation, evaluating model fit using χ^2, CFI, TLI, RMSEA, and SRMR against thresholds recommended by Kline (2023). Reflective constructs were modelled as latent variables; formative composites (insurance coverage breadth, verification stringency, preventive resilience investment) were treated as observed composite indicators in the CB-SEM model to maintain comparability with the PLS-SEM specification, following Sarstedt et al. (2022). Because formative composites are treated as observed composite indicators in this specification, CB-SEM global fit indices are reported for transparency but are not interpreted as a decisive robustness test of the structural theory.

A potential concern with cross-sectional survey evidence on the coverage–moral hazard–investment chain is endogeneity in coverage choice: firms with broader coverage may differ systematically from firms with narrower coverage on dimensions correlated with both moral hazard and preventive investment, such as risk exposure, supply chain complexity, organisational risk-management maturity, and prior loss experience (Antonakis et al. 2010; Cohen and Siegelman 2010). The proposed research design and analysis reduce this concern in two ways, although neither eliminates it. First, the sampling frame is restricted to firms that already hold supply chain insurance coverage, which removes the binary insurance-participation margin and focuses the analysis on variation in coverage breadth among insured firms. Second, the focal mechanism, managerial moral hazard perceptions, is measured separately from coverage breadth and preventive resilience investment, reducing the most direct forms of common-source bias affecting the indirect pathway (Podsakoff et al. 2024). Because the data are cross-sectional and observational, all estimates are interpreted as theoretically consistent associations among coverage breadth, moral hazard perceptions, preventive resilience investment, and perceived disruption impact, not as causal treatment effects of insurance coverage breadth. Unobserved heterogeneity may nevertheless remain. As a supplementary sensitivity check, the structural model was also re-estimated with available firm-level covariates, including supply chain complexity, prior disruptions, insurance tenure, and prior claims. Because the design is cross-sectional, all hypotheses are tested and interpreted as directional associations.

4. Results

4.1. Measurement Model

Reflective constructs (visibility, moral hazard perceptions, perceived disruption impact) demonstrated adequate reliability and convergent validity. Table 3 summarizes the measurement model assessment. All item loadings exceeded 0.70; composite reliabilities (CR) ranged from 0.916 to 0.925, well above the 0.70 threshold; and average variance extracted (AVE) ranged from 0.692 to 0.731, above the 0.50 threshold (Hair et al. 2019). Cronbach's alpha values (0.877–0.898) indicated good internal consistency, and Dijkstra–Henseler's rho_A values (0.879–0.901) confirmed reliability under conditions specific to PLS-SEM (Henseler et al. 2015). Discriminant validity was assessed using the heterotrait–monotrait ratio (HTMT) approach; all HTMT values were below the conservative 0.85 threshold (max HTMT = 0.22), supporting discriminant validity. For the formative composites—insurance coverage breadth, verification stringency, and preventive resilience investment—multicollinearity was assessed through variance inflation factors across their respective indicators. The maximum VIF was 3.08 for ICB6, well below the threshold of 5.00 (Hair et al. 2019). We retained all indicators given their theoretical importance and acceptable multicollinearity. Outer weights for all formative indicators were significant at $p < 0.01$. Convergent consistency of the exploratory risk-type measure was assessed against the second confirmatory item. The standardized preventable-risk share and the confirmatory item were strongly correlated (r = 0.842, $p < 0.001$) and agreed on the dominant risk category in 94.2% of non-neutral cases (n = 172). This indicates that risk type was captured reliably despite its simpler operationalisation, although it remains exploratory rather than a fully validated multi-item construct.

Table 3. *Measurement model assessment for reflective constructs.*

Construct	Items	Loading Range	AVE	CR	α	rho_A
Visibility (VIS)	5	0.812–0.843	0.692	0.918	0.889	0.892
Moral Hazard perceptions (MH)	4	0.816–0.887	0.731	0.916	0.877	0.879
Perceived Disruption Impact (DI)	5	0.813–0.867	0.710	0.925	0.898	0.901

Note. *AVE = average variance extracted; CR = composite reliability; α = Cronbach's alpha; rho_A = Dijkstra–Henseler's rho. MH denotes the perceptual moral hazard measure; DI denotes perceived disruption impact.*

4.2. Structural Model

The PLS-SEM results support the central moral hazard mechanism proposed in this study. Table 4 reports the bootstrapped structural model estimates, including standardized path coefficients, standard errors, t-values, *p*-values, confidence intervals, effect sizes, and hypothesis decisions.

Table 4. *PLS-SEM structural model—bootstrap results.*

Hyp.	Path	β	SE	t	*p*	95% CI	f^2	Decision
H1	ICB → MH	+0.406	0.061	6.65	<0.001	[0.289, 0.529]	0.184	Supported
H2	MH → PRI	−0.275	0.068	4.03	<0.001	[−0.411, −0.145]	0.082	Supported
H3	PRI → DI	−0.277	0.059	4.66	<0.001	[−0.395, −0.160]	0.083	Supported
H4	ICB → MH → PRI (indirect)	−0.112	0.034	3.33	<0.001	[−0.186, −0.054]	—	Supported
	ICB → PRI (direct)	−0.082	0.062	1.31	0.189	[−0.203, +0.042]	0.007	Not significant
	ICB → PRI total effect	−0.194	0.060	−3.22	0.001	[−0.314, −0.074]	—	Significant
H5a	VIS × ICB → MH	−0.107	0.050	2.13	0.033	[−0.208, −0.011]	0.015	Supported (small)
H5b	VER × ICB → MH	−0.150	0.058	2.60	0.009	[−0.271, −0.041]	0.031	Supported (small)
	RT × ICB → MH	+0.101	0.062	1.63	0.103	[−0.022, +0.220]	0.014	Exploratory; directional but inconclusive

Note. *β = standardized path coefficient; SE = bootstrap standard error; CI = bias-corrected and accelerated confidence interval; f^2 = Cohen's effect size. MH denotes the perceptual moral hazard measure; DI denotes perceived disruption impact. The risk-type interaction is reported as an exploratory test rather than as a confirmatory hypothesis.*

As shown in Table 4, insurance coverage breadth was positively associated with moral hazard perceptions (β = 0.406, t = 6.65, $p < 0.001$), supporting H1. Moral hazard perceptions were negatively associated with preventive resilience investment (β = −0.275, t = 4.03, $p < 0.001$), supporting H2. Preventive resilience investment was also negatively associated with perceived disruption impact (β = −0.277, t = 4.66, $p < 0.001$), supporting H3. These results indicate that broader insurance coverage is associated with stronger moral hazard perceptions, which in turn are linked to lower preventive resilience investment and greater disruption consequences.

Figure 2 presents the PLS-SEM structural model with standardized path coefficients and R^2 values for the endogenous constructs. The figure visually confirms the positive path from insurance coverage breadth to moral hazard perceptions, as well as the negative downstream paths from moral hazard perceptions to preventive resilience investment and from preventive resilience investment to perceived disruption impact.

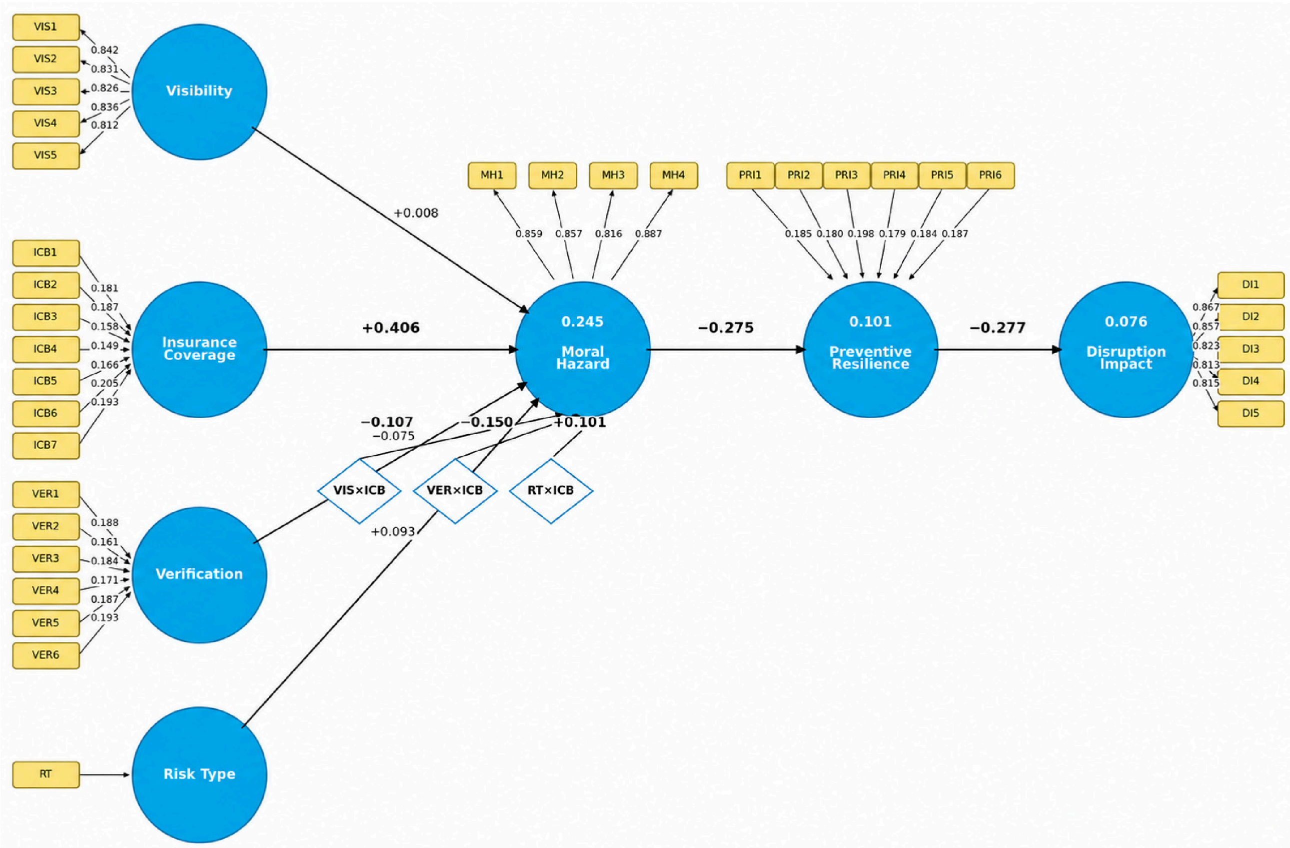

Figure 2. PLS-SEM standardized path coefficients.

The mediation results provide further evidence for the proposed behavioural mechanism. As reported in Table 4, the indirect effect of insurance coverage breadth on preventive resilience investment through moral hazard perceptions was negative and statistically significant ($\beta = -0.112$, $p < 0.001$, 95% CI [−0.186, −0.054]), supporting H4. The direct effect of insurance coverage breadth on preventive resilience investment was not statistically significant ($\beta = -0.082$, $p = 0.189$). The total effect of insurance coverage breadth on preventive resilience investment was negative and statistically significant ($\beta = -0.194$, SE = 0.060, t = 3.22, $p = 0.001$, 95% CI [−0.314, −0.074]). The finding is, therefore, interpreted as indirect-only mediation, with moral hazard perceptions accounting for approximately 57% of the total effect.

Figure 3 presents the bootstrapped t-values for the PLS-SEM structural paths. The figure complements Table 4 by showing which paths exceed the conventional significance threshold and confirms the significance of H1, H2, H3, H4, H5a, and H5b, while showing that the exploratory risk-type interaction does not reach the 5% significance level.

The moderation results indicate that the coverage–moral hazard relationship depends partly on the conditions under which insurance operates. As shown in Table 4, supply chain visibility was associated with a weaker positive relationship between insurance coverage breadth and moral hazard perceptions ($\beta = -0.107$, t = 2.13, $p = 0.033$), supporting H5a, although the effect size was very small ($f^2 = 0.015$). Firm-perceived insurer verification stringency produced a stronger moderating effect ($\beta = -0.150$, t = 2.60, $p = 0.009$), supporting H5b. Both f^2 values fall at or below Cohen's small-effect benchmark; with n = 241, these interactions are statistically detectable but of limited practical magnitude. We therefore interpret them as modest attenuation effects rather than managerially large moderators. By contrast, the exploratory interaction between risk type and insurance coverage breadth was positive but not statistically significant at the conventional 5% level ($\beta = +0.101$, $t = 1.63$, $p = 0.103$). This result is, therefore, interpreted as directionally consistent but statistically inconclusive, not as support for a confirmatory hypothesis.

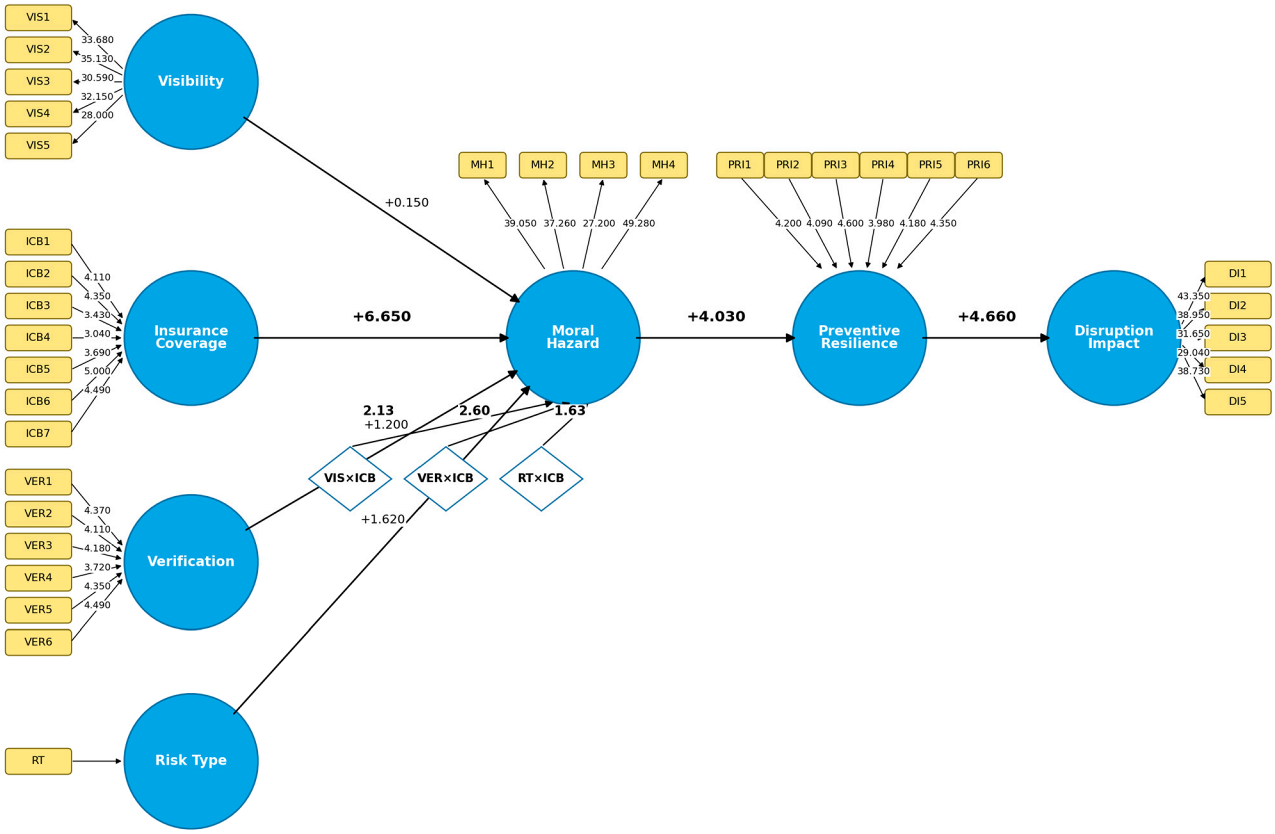

Figure 3. PLS-SEM model with bootstrap t-values (5000 resamples).

The model explained 24.5% of the variance in moral hazard, 10.1% of the variance in preventive resilience investment, and 7.6% of the variance in disruption impact. These R^2 values are modest—and low in absolute terms for preventive resilience investment (10.1%) and perceived disruption impact (7.6%)—and should be interpreted cautiously. The model is, therefore, best understood as testing a specific incentive pathway rather than as providing a comprehensive explanation of disruption consequences. Perceived disruption impact is likely shaped by other factors outside the proposed chain, including event type, supply-base complexity, prior disruption exposure, claims history, operational slack, and macro-institutional conditions. Accordingly, the model should not be interpreted as a predictive model of overall disruption severity; its contribution is limited to testing the proposed insurance–moral hazard–prevention pathway. Cross-validated predictive relevance values were positive for all endogenous constructs: $Q^2 = 0.176$ for moral hazard perceptions, $Q^2 = 0.085$ for preventive resilience investment, and $Q^2 = 0.066$ for perceived disruption impact. Model fit was also acceptable, with SRMR = 0.058, which is below the recommended 0.08 threshold. Full-collinearity VIF values ranged from 1.011 to 1.245, remaining well below the 3.3 threshold suggested in the literature (Kock 2015; Shojaei et al. 2026a). In addition, Harman's single-factor test indicated that the first unrotated factor accounted for 21.7% of the total variance, well below the 50% threshold, providing further evidence that common method bias is unlikely to dominate the results. However, because full-collinearity VIFs and Harman's test do not fully detect evaluative-consistency or social-desirability bias, these diagnostics are treated as supplementary rather than conclusive and are complemented by the unmeasured latent method-factor analysis reported in Section 4.3. Figure 4 illustrates the three moderation effects using simple-slope plots. The plots show that the coverage–moral hazard relationship is weaker at higher levels of supply chain visibility and verification stringency, with the verification effect appearing more pronounced. The risk-type plot shows the expected directional pattern, but the slope difference is not statistically conclusive.

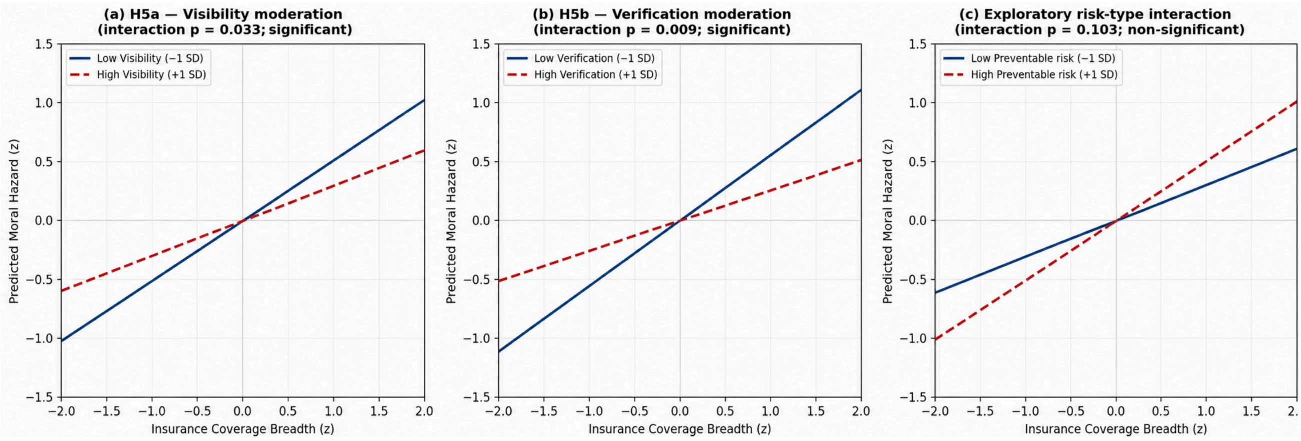

Figure 4. Simple-slope plots for moderation effects.

4.3. Estimator-Sensitivity and Supplementary Diagnostic Checks

Although PLS-SEM is the primary estimator for the present model—given the formative composites and the prediction-oriented framing—CB-SEM is reported as an estimator-sensitivity check. This check is useful for assessing whether the signs and approximate magnitudes of the structural paths are stable under a different estimation philosophy (Kline 2023). However, because the formative composites are represented as observed composite indicators in the CB-SEM specification, global fit indices are reported only for transparency and are not treated as a strong test of the structural theory.

CB-SEM estimation produced standardized path coefficients that were directionally consistent with the PLS-SEM results, as reported in Table 5. The three core hypotheses (H1, H2, H3) and the verification moderation (H5b) reached significance at $p < 0.01$ under both estimation approaches. The visibility moderation (H5a) reached significance at $p < 0.05$ under both approaches. The exploratory risk-type interaction was marginal in CB-SEM ($p = 0.061$), but non-significant in PLS-SEM ($p = 0.103$). Because risk type is no longer treated as a confirmatory hypothesis, this pattern is interpreted only as directional and exploratory; it does not provide confirmatory support for a risk-type boundary condition.

The CB-SEM model produced the same directional pattern as the PLS-SEM model, but its global fit indices are not treated as substantive robustness evidence. Because formative composites were represented as observed composite indicators, the model is close to saturated at the covariance level, making χ^2, CFI, TLI, and RMSEA overly favourable and weakly diagnostic. We therefore report these indices only for transparency: $\chi^2(192) = 144.07$, $p = 0.996$; CFI = 1.00; TLI = 1.00; RMSEA = 0.000; and SRMR = 0.058. The estimator-sensitivity value of the CB-SEM analysis lies in the stability of path signs and approximate magnitudes, not in the global fit statistics. Figure 5 presents the CB-SEM model with standardized path estimates.

Table 5. *Covariance-based SEM standardized structural estimates: estimator-sensitivity check.*

Hyp.	Path	β (Std)	SE	z	p	Decision
H1	ICB → MH	+0.431	0.065	6.61	<0.001	Supported
H2	MH → PRI	−0.318	0.075	4.26	<0.001	Supported
H3	PRI → DI	−0.287	0.066	4.33	<0.001	Supported
H4	ICB → MH → PRI (indirect)	−0.137	0.043	3.20	0.001	Supported; indirect effect significant
H5a	VIS × ICB → MH	−0.125	0.062	2.03	0.043	Supported; very small effect
H5b	VER × ICB → MH	−0.173	0.062	2.77	0.006	Supported; small effect
—	RT × ICB → MH	+0.113	0.060	1.88	0.061	Exploratory; marginal but inconclusive

Note. *Standardized maximum-likelihood estimates are reported. Formative composites (ICB, VER, PRI) were represented as observed composite indicators. SE denotes the standard error of the standardized estimate; z-values are reported as absolute critical ratios;* p*-values are two-tailed. CB-SEM is used only as an estimator-sensitivity check, not as a decisive model-fit test. ICB = insurance coverage breadth; MH = moral hazard perceptions; PRI = preventive resilience investment; DI = perceived disruption impact; VIS = supply chain visibility; VER = verification stringency; RT = risk type.*

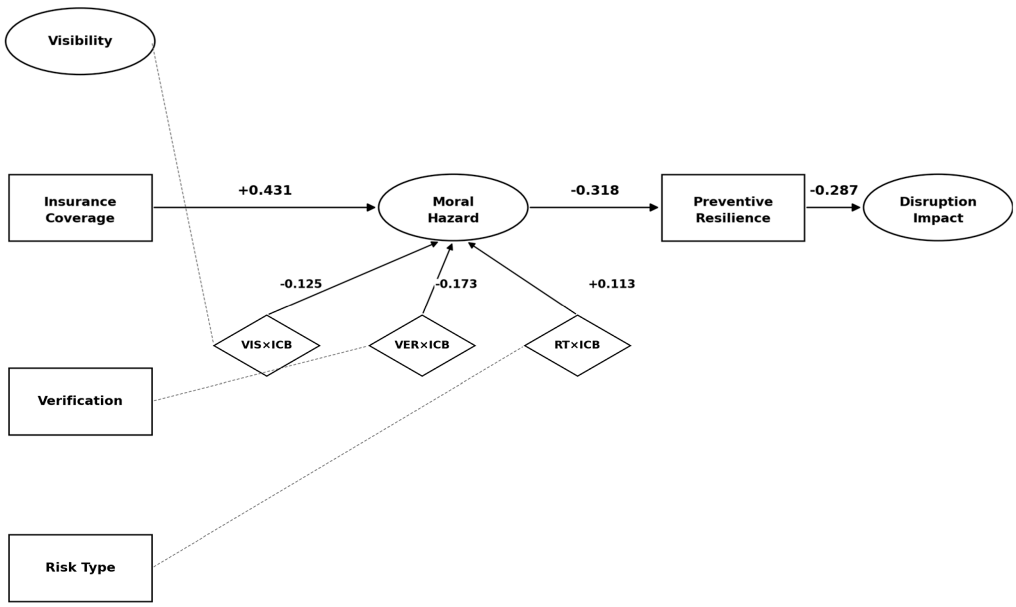

Figure 5. CB-SEM standardized maximum-likelihood estimates.

To address evaluative-consistency bias in the focal moral hazard perception–preventive resilience investment path, an unmeasured latent method-factor analysis was conducted in which all reflective indicators were allowed to load on both their substantive construct and a common method factor. The focal path remained negative and significant after including the method factor (β = −0.252, p = 0.005), indicating that the result is not fully explained by a common method factor. Because preventive resilience investment is modelled as a formative composite, this diagnostic is treated as supplementary rather than as a full item-level correction for method variance across all PRI indicators.

As an additional sensitivity check, the MH → PRI path was re-estimated among respondents who rated their insurance-domain knowledge highly on the informant self-competency item (K2 ≥ 6 on a seven-point scale, n = 107). The coefficient remained negative and significant (β = −0.441, p < 0.001). In the risk/insurance-manager subsample (n = 55), the coefficient also remained negative (β = −0.197), but was not statistically significant (p = 0.133), consistent with reduced power in the smaller subsample. These checks suggest that the focal MH → PRI association is not confined to less-informed respondents, although the evidence remains based on single-respondent survey data.

As a further covariate-adjusted sensitivity check, the structural model was re-estimated controlling for four firm-level covariates available in the data: supply chain complexity, prior disruptions, insurance tenure, and prior claims. This check addresses the concern that omitted risk exposure, insurance history, or prior loss experience may confound the focal relationships. The pattern remained stable: ICB → MH (β = 0.402, $p < 0.001$), MH → PRI (β = −0.266, $p < 0.001$), and PRI → DI (β = −0.298, $p < 0.001$). There was a significant negative indirect effect of coverage breadth on preventive investment through moral hazard perceptions (β = −0.107, 95% CI [−0.177, −0.049]) and a non-significant direct effect (β = −0.062, $p = 0.358$). The verification interaction remained significant (VER × ICB → MH: β = −0.165, $p = 0.006$), whereas the visibility interaction weakened to marginal significance (VIS × ICB → MH: β = −0.100, $p = 0.096$), consistent with its already small effect size. These results suggest that the main findings are not driven by observable differences in firm risk exposure, insurance history, or prior disruption experience.

Following PLS-SEM power-assessment guidance (Kock and Hadaya 2018), a closed-form sensitivity power calculation was conducted for the reported interaction effects at N = 241 and α = 0.05. A full model-calibrated Monte Carlo power study was not undertaken because the present model combines formative composites with composite-based interaction terms; such a design would require a bespoke composite-based simulation specification rather than a generic factor-model routine (Aguirre-Urreta and Rönkkö 2015). The sensitivity calculation is, therefore, reported as a finite-sample diagnostic, and a bespoke composite-based Monte Carlo simulation is identified as a useful validation step for future work. The verification interaction showed approximately 78% power, whereas the visibility and exploratory risk-type interactions showed approximately 47% and 41% power, respectively. These results support a cautious interpretation of the moderation findings: the verification interaction is comparatively more stable, while the visibility and risk-type interactions should be treated as preliminary and replicated in larger samples, ideally using longitudinal designs and bespoke composite-based Monte Carlo assessment.

Across these estimator-sensitivity, covariate-adjusted sensitivity, and supplementary diagnostic checks, the main hypothesis-decision pattern remains stable: H1, H2, H3, H4, and H5b are supported; H5a is supported with a very small effect that attenuates to marginal under covariate adjustment; and the exploratory risk-type interaction is directionally consistent but statistically inconclusive. The cross-check consistency increases confidence in the stability of the estimated associations. Table 6 summarizes the hypothesis-decision pattern across both estimation methods.

Table 6. *Hypothesis decision summary across estimation methods.*

Hyp.	Statement	PLS-SEM	CB-SEM	Overall Decision
H1	ICB → MH (positive)	β = 0.41 ***	β = 0.43 ***	Supported
H2	MH → PRI (negative)	β = −0.28 ***	β = −0.32 ***	Supported
H3	PRI → DI (negative)	β = −0.28 ***	β = −0.29 ***	Supported
H4	ICB → MH → PRI (mediation)	ind = −0.11 ***	ind = −0.14 **	Supported; indirect-only mediation, VAF = 57%
H5a	VIS × ICB → MH	β = −0.11 *	β = −0.13 *	Supported (very small effect); attenuates to marginal under covariate adjustment
H5b	VER × ICB → MH	β = −0.15 **	β = −0.17 **	Supported; small effect
—	RT × ICB → MH (exploratory)	β = +0.10 ($p = 0.103$)	β = +0.11 ($p = 0.061$)	Exploratory; directional but inconclusive

Note. *Three asterisks denote p < 0.001, two asterisks p < 0.01, and one asterisk p < 0.05. MH denotes the perceptual moral hazard measure; DI denotes perceived disruption impact; RT denotes risk type. The risk-type interaction is exploratory and is not treated as a confirmatory hypothesis.*

5. Discussion

5.1. Theoretical Implications

The results support the proposed incentive pathway linking insurance coverage breadth, moral hazard perceptions, preventive resilience investment, and perceived disruption impact. H1 indicates that insurance coverage breadth is positively associated with moral hazard perceptions (β = 0.406, $p < 0.001$). This finding suggests that broader insurance coverage is associated with stronger managerial perceptions that insurance reduces the urgency of preventive safeguards.

H2 indicates that moral hazard perceptions are negatively associated with preventive resilience investment (β = −0.275, $p < 0.001$). This finding is important because preventive resilience actions, such as backup suppliers, safety stock, supplier qualification, geographic diversification, and risk-monitoring systems, require upfront resources, while their benefits are uncertain and often visible only during disruption events. The result suggests that when managers perceive insurance as absorbing a substantial part of disruption-related losses, the incentive to maintain costly preventive safeguards may weaken.

Results for H3 show that preventive resilience investment is negatively associated with perceived disruption impact (β = −0.277, $p < 0.001$). This finding should be read cautiously because disruption impact is measured as a self-reported perception of disruption consequences and the R^2 for this outcome is modest. The result therefore supports the expected direction between preventive resilience and perceived disruption consequences, but it does not show that insurance design explains objective disruption losses.

H4 further shows that moral hazard perceptions mediate the ICB–PRI association, while the direct ICB–PRI path is not significant. The total effect of ICB on PRI is also negative and significant (β = −0.194, $p = 0.001$). Taken together, these findings support an indirect incentive pathway: broader coverage is associated with lower preventive investment mainly through managers' perceptions that insurance reduces the urgency of prevention, not through a simple direct substitution effect.

Results for H5a and H5b show that supply chain visibility and firm-perceived insurer verification stringency are associated with a weaker coverage–moral hazard perception relationship. The visibility effect is statistically significant but very small in the primary estimators, and attenuates to marginal once firm-level covariates are added, whereas the verification effect is stronger and remains significant under covariate adjustment. This suggests that information visibility alone may not preserve prevention incentives unless it is connected to governance, audit, certification, or renewal requirements. The result also supports this paper's incentive-design argument: monitoring matters most when it is attached to contractual consequences.

Risk type is treated as an exploratory boundary condition rather than as a formal hypothesis. Its positive but non-significant interaction suggests a possible stronger moral hazard perception pattern when firms face risks that are more preventable through internal effort, such as supplier-qualification failures or cyber-hygiene lapses, but the evidence is not strong enough to confirm this boundary condition. Because the risk-type measure shows convergent consistency with the confirmatory item, the inconclusive result is best interpreted as evidence of a small or absent moderating effect rather than as clear measurement failure. Future research should examine whether the moral hazard perception mechanism differs across more precise disruption-risk categories.

5.2. Managerial and Policy Implications

For supply chain managers, and based on evidence from this single emerging-market manufacturing setting, the findings suggest that insurance coverage decisions should be reviewed alongside internal resilience-investment routines. The evidence does not show that broader coverage causes objective disruption losses; rather, it indicates that broader perceived protection is associated with lower prevention urgency. Firms can reduce this risk by linking periodic insurance reviews—such as policy renewal, coverage expansion, or claims-review meetings—to documented resilience commitments, including supplier qualification, contingency planning, safety-stock policies, and risk-monitoring routines.

For insurers, and according to evidence from this emerging-market setting, the verification result is consistent with the long-standing principle that conditioning coverage on observable behaviour can preserve prevention incentives, but it extends this principle into a domain, supply chain coverage, where verification has historically been weaker than in physical-property lines. The current trend toward parametric and visibility-based insurance products (Lawrence et al. 2023; Dutta et al. 2023) may be more effective when combined with verification requirements, similar to more conventional insurance lines such as auto insurance, where telematics-based monitoring links coverage conditions to observed policyholder behaviour (Holzapfel et al. 2024). Subject to replication in other contexts, insurers seeking to underwrite supply chain risk profitably should consider whether their underwriting questionnaires meaningfully condition coverage on demonstrated resilience practices, rather than treating these as informational only. This points toward a more active monitoring role for the insurer, potentially supported by InsurTech platforms that connect insurer systems to supplier-mapping tools (Cappiello 2020).

For policymakers, and subject to replication in other institutional and insurance markets, the findings have implications for currently debated supply chain resilience initiatives. To the extent that public policy seeks to encourage firms to invest in preventive resilience, insurance market design matters. Mandates or incentives that encourage broad coverage without commensurate verification may unintentionally reduce perceived prevention urgency, particularly where insurance coverage is treated as a substitute for internal resilience routines.

6. Conclusions, Limitations, and Future Research

This study examined whether broader supply chain insurance coverage is associated with lower preventive resilience investment through perceived managerial moral hazard. Using cross-sectional survey data from 241 managers in Iranian manufacturing-intensive firms and applying PLS-SEM with estimator-sensitivity, covariate-adjusted sensitivity, and supplementary diagnostic checks, the results support a bounded associational pattern: coverage breadth is positively related to moral hazard perceptions; moral hazard perceptions are negatively related to preventive resilience investment; and preventive resilience investment is negatively related to perceived disruption impact. The total effect of insurance coverage breadth on preventive resilience investment is also negative and significant. Firm-perceived insurer verification stringency is associated with a weaker coverage–moral hazard perception relationship and appears more informative than supply chain visibility, although both moderation effects are small. These findings extend moral hazard reasoning to supply chain insurance cautiously by focusing on perceptions and prevention incentives rather than objective loss behaviour.

The findings should be interpreted in light of several limitations. First, the cross-sectional and observational design cannot rule out endogeneity in coverage choice, and the estimates should not be read as causal treatment effects. Although the sample is restricted to firms already holding supply-chain-relevant insurance coverage, which removes the binary insurance-participation margin, unobserved differences in coverage breadth may remain. Second, moral hazard is measured as perceived reduction in prevention urgency, not as observed behavioural moral hazard or post-loss prevention effort. Third, disruption impact is measured through managers' recall-based perceptions rather than objective event-level loss data; this is especially important because the model explains only a small share of the variance in preventive resilience investment (R^2 = 10.1%) and perceived disruption impact (R^2 = 7.6%). The structural relationships should therefore be read as evidence on the direction of a specific incentive mechanism, not as a predictive model of either outcome. Fourth, broad nominal coverage may not equate to credible financial protection where payout capacity is constrained. This limitation bounds the expected-indemnification strength of the mechanism rather than the perceptual mechanism itself: managers may adjust prevention urgency in response to perceived insurance protection even when eventual payout is uncertain or incomplete. To the extent that the insurance coverage breadth construct captures formal policy ownership rather than expected indemnification, the substitution incentive operating through actual indemnification may be attenuated. Fifth, the single-respondent design creates common method and evaluative-consistency concerns, particularly for the moral hazard perception–preventive resilience investment path. Although procedural remedies and supplementary diagnostics reduce this concern, they do not eliminate it. Relatedly, the finite-sample assessment relies on closed-form sensitivity power calculations rather than a model-calibrated Monte Carlo simulation for formative composites and composite-based interactions. The moderation results, especially visibility and risk type, should therefore be interpreted as preliminary and replicated in larger samples. Sixth, the Iranian manufacturing setting limits external validity; the results should be generalised only cautiously to other institutional and insurance-market contexts, given the distinctive structure and development trajectory of Iran's insurance industry (Shojaei and Almansour 2025). This caveat is particularly relevant for mature OECD markets, where insurance-market structure, risk-allocation mechanisms, and policy implications may differ from emerging insurance settings (Shojaei et al. 2026b). Seventh, firm-perceived insurer verification stringency is measured from the insured firm's perspective rather than from insurer underwriting records. The VER indicators (Table 2) capture whether respondents believe insurers require audits, certifications, continuity plans, supplier mapping, supplier risk assessments, and renewal reviews; they do not verify whether insurers actually imposed, audited, enforced, or priced these requirements. The verification result should therefore be interpreted as evidence about perceived verification architecture, not as direct evidence about insurer-side underwriting practice. Finally, risk type is measured with a simpler risk-allocation approach, so the inconclusive exploratory result should be replicated using richer risk-profile measures. Future research should use longitudinal designs, insurer-side records, paired respondents, objective disruption-loss data, and cross-country samples to test whether the same mechanism appears in mature and emerging insurance markets.

Taken together, and within the bounds of this emerging-market manufacturing setting, the findings reposition insurance not merely as a post-loss financing instrument but as a design variable that may shape ex ante prevention incentives. The resilience value of supply chain insurance appears to depend not only on the breadth of coverage but also on the verification architecture surrounding it: coverage that is coupled to documented preventive practice may help preserve incentives, whereas coverage extended without such coupling may be associated with lower perceived prevention urgency. Future work linking insurer underwriting records to firm-level prevention data, and observing behaviour across policy-renewal cycles, would allow this incentive-design perspective to be tested causally and extended beyond the present setting.

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