Granularity, Mutualization, and AI Risk in Insurance

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(AI Revolution and Cyber Risks Session)

Granularity and Mutualization

Turning heterogeneity into risk classes

- Variance decomposition, for some latent risk factor Θ,

$$\text{Var}[Y] = \underbrace{\mathbb{E}[\text{Var}[Y|\Theta]]}_{\text{within}} + \underbrace{\text{Var}[\mathbb{E}[Y|\Theta]]}_{\text{between}}.$$

- In practice, insurers observe only a vector of covariates $\boldsymbol{X}$,

$$\text{Var}[Y] = \underbrace{\mathbb{E}[\text{Var}[Y|\boldsymbol{X}]]}_{\to\text{ insurer}} + \underbrace{\text{Var}[\mathbb{E}[Y|\boldsymbol{X}]]}_{\to\text{ policyholder}}.$$

- The residual uncertainty decomposes as

$$\mathbb{E}[\text{Var}[Y|\boldsymbol{X}]] = \underbrace{\mathbb{E}[\text{Var}[Y|\Theta]]}_{\text{irreducible risk}} + \underbrace{\mathbb{E}[\text{Var}[\mathbb{E}[Y|\Theta]|\boldsymbol{X}]]}_{\textbf{epistemic uncertainty}}.$$

- [De Pril and Dhaene, 1996] interpret this distinction as the difference between random solidarity and subsidiary solidarity, while [Charpentier and Denuit, 2004, Charpentier and Denuit, 2005, Antonio and Valdez, 2012] show how observable heterogeneity is translated into tariff classes.

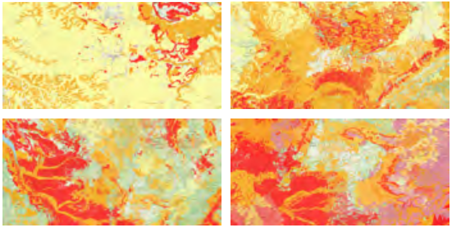
Information asymmetry: private information and selection

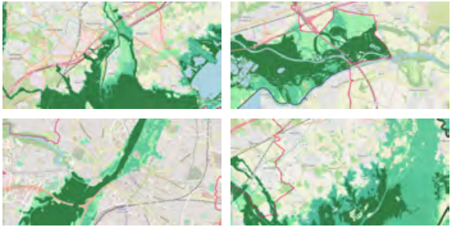
- Insurance markets are vulnerable to asymmetric information: when policyholders know more about their risk than insurers, pooling contracts may attract high-risk types and destabilize the market [Akerlof, 1970, Rothschild and Stiglitz, 1976].
- Empirical tests of asymmetric information ask whether coverage choices still predict losses after controlling for observable risk characteristics [Chiappori and Salanié, 2000].
- Genetic information made this problem especially visible: private knowledge about future health risks can undermine mutualization even before any claim occurs [Hoy and Polborn, 2000, Lehtonen and Liukko, 2011].
- Risk-classification bans can protect individuals against reclassification risk, but they also change participation, cross-subsidies, and market equilibrium [Dionne and Rothschild, 2014].
- The classical concern is therefore not too much information, but unequal access to information.

Information granularity: reducing epistemic uncertainty?

- Granular information reduces epistemic uncertainty by making latent heterogeneity partially observable [Bühlmann and Gisler, 2005].
- More variables, finer spatial resolution, telematics, genetic data, and behavioural traces all make it easier to replace pooled uncertainty by classified heterogeneity [Eling et al., 2022].
- But finer classification does not only improve prediction: it also redistributes premiums, changes participation, and may weaken the social meaning of insurance [Lehtonen and Liukko, 2011].
- Removing protected variables is not enough, because granular covariates may reconstruct protected or socially sensitive information [Lindholm et al., 2022a, Lindholm et al., 2022b, Charpentier, 2024].
- Granularity also raises inclusive-insurance issues: some predictive information may be accurate but should fade over time, as in debates on criminal records, rehabilitation, and the right to be forgotten [Charpentier and Schraub, 2026].

Natural catastrophe maps: pricing granularity and withdrawal





Source: https://www.georisques.gouv.fr/cartes-interactives/

- Vulnerability maps turn spatial heterogeneity into observable and increasingly priceable risk classes [Dalbarade et al., 2026].
- Even when natural catastrophe coverage is formally pooled, access to insurance may depend on the underlying household contract.
- Granular pricing can attract low-risk households, while high-risk areas face higher premiums, stricter conditions, or localized non-quoting.
- The key regulatory object is therefore not only the average premium, but also local availability, insurer presence, and effective withdrawal.

Actuarial fairness: fairness relative to information

- Actuarial fairness is usually defined by the idea that equal risks should pay equal premiums [Charpentier, 2024].
- But "equal risks" depends on the information set: full profile, tariff class, score, group, or protected attribute.
- Coarser information gives weaker notions of fairness: global balance, calibration by score, calibration by group, or full risk-based pricing [Charpentier et al., 2026a].
- [Charpentier et al., 2026b] frame the resulting tension as a trilemma between actuarial adequacy ("actuarial fairness")), solidarity ("cross-subsidies"), and causal legitimacy.

AI Risk in Insurance

From AI for insurance to insurance for AI

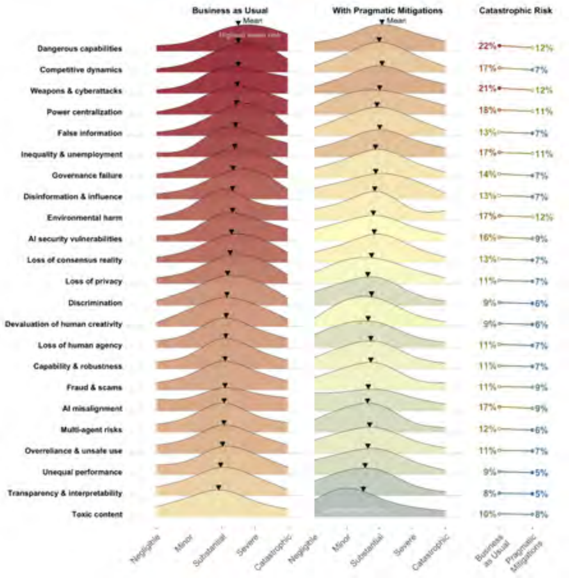
- AI is not only a tool used by insurers; it is also becoming an insured exposure embedded in firms, products, services, and professional decisions [Szpruch et al., 2025].
- Many AI losses will first appear through familiar insurance lines: cyber, technology E&O, professional liability, product liability, D&O, and regulatory risk.
- What is new is the combination of opacity, scale, speed, model updates, and difficult ex-post attribution.
- The actuarial question is therefore not simply whether AI is risky, but whether the risk can be bounded, observed, priced, monitored, and evidenced.

Common models, common failures

- AI creates accumulation risk : portfolios may look diversified by sector or geography while depending on the same models, APIs, clouds, datasets, or agent frameworks [Charpentier, 2026a].
- A model update, data poisoning event, prompt-injection vulnerability, retrieval failure, or compromised API can affect many insureds at once.
- This weakens the usual law-of-large-numbers intuition: losses may be synchronized by shared technological infrastructure .
- Underwriting therefore requires a map of the AI supply chain: provider, model version, cloud, API, data source, retrieval system, tools, agents, and change-management process.

Prioritizing AI risks: severity, vulnerability, responsibility

- [Saeri et al., 2026] use a Delphi study of 272 international experts to rank 24 AI risk domains by severity, likelihood, vulnerability, and responsibility.
- Under a business-as-usual scenario, experts judge 18 of the 24 domains to have more than a 10% probability of catastrophic outcomes by 2030.
- For insurance, the key message is the mismatch between vulnerability and control : users and affected stakeholders are most exposed, while developers, regulators, governments, and standards bodies are seen as most responsible.



LLMs: plausible outputs, costly verification

- LLM failures are not limited to hallucinations: they include retrieval errors, prompt injection, privacy leakage, biased outputs, insecure code, and incorrect tool use [Bender et al., 2021, Bommasani et al., 2021, Weidinger et al., 2021].
- Benchmarks evaluate controlled tasks, while insurance must deal with deployed systems, incentives, changing environments, and downstream losses [Bengio et al., 2025a, Bengio et al., 2025b].
- AI systems often shift the cost of reliability from production to verification: outputs are cheap, but checking them may be expensive.
- A human-in-the-loop is not a control unless the human has time, competence, authority, and incentives to challenge the model output [Elish, 2019].

Proof, traceability, and insurability

- Insurance can make proof financially relevant: coverage may depend on logs, audits, monitoring, incident reporting, and documented controls [National Institute of Standards and Technology, 2023, OECD, 2025].
- The insured system must be defined: use case, model, version, provider, data source, retrieval layer, tools, agents, and update regime.
- Governance must be operational, not symbolic: checklists do not prove that controls were active when the loss occurred [Raji et al., 2020, Mitchell et al., 2019].
- Conditional insurability follows: bounded, documented, monitored AI may be insurable; autonomous, opaque, unlogged AI may require exclusions, sublimits, or refusal.

From “code is law” to “vibe code is liability”

- [Lessig, 1999] famously argued that “code is law”. It means that software does not merely execute rules; it also shapes behavior by defining what users can do, what they cannot do, what is easy or costly, and what remains visible or hidden.
- Vibe coding turns software risk into provenance risk: after a loss, can the insured reconstruct the path from prompt to production [Charpentier, 2026b]?
- AI-generated code creates a software supply-chain exposure: prompts, model versions, generated diffs, tests, dependencies, permissions, and approvals become part of the risk record.
- The underwriting question is not only “Do you use AI?”, but “How can AI-generated code enter production?”
- Policy tools include approved-tool representations, retained logs, mandatory review, vulnerability scanning, SBOM updates, exclusions for unreviewed autonomous deployment, and aggregation clauses for common model or tool failures [Sculley et al., 2015, Pearce et al., 2021].

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Insurance in the Age of AI

A report series of the Geneva Association

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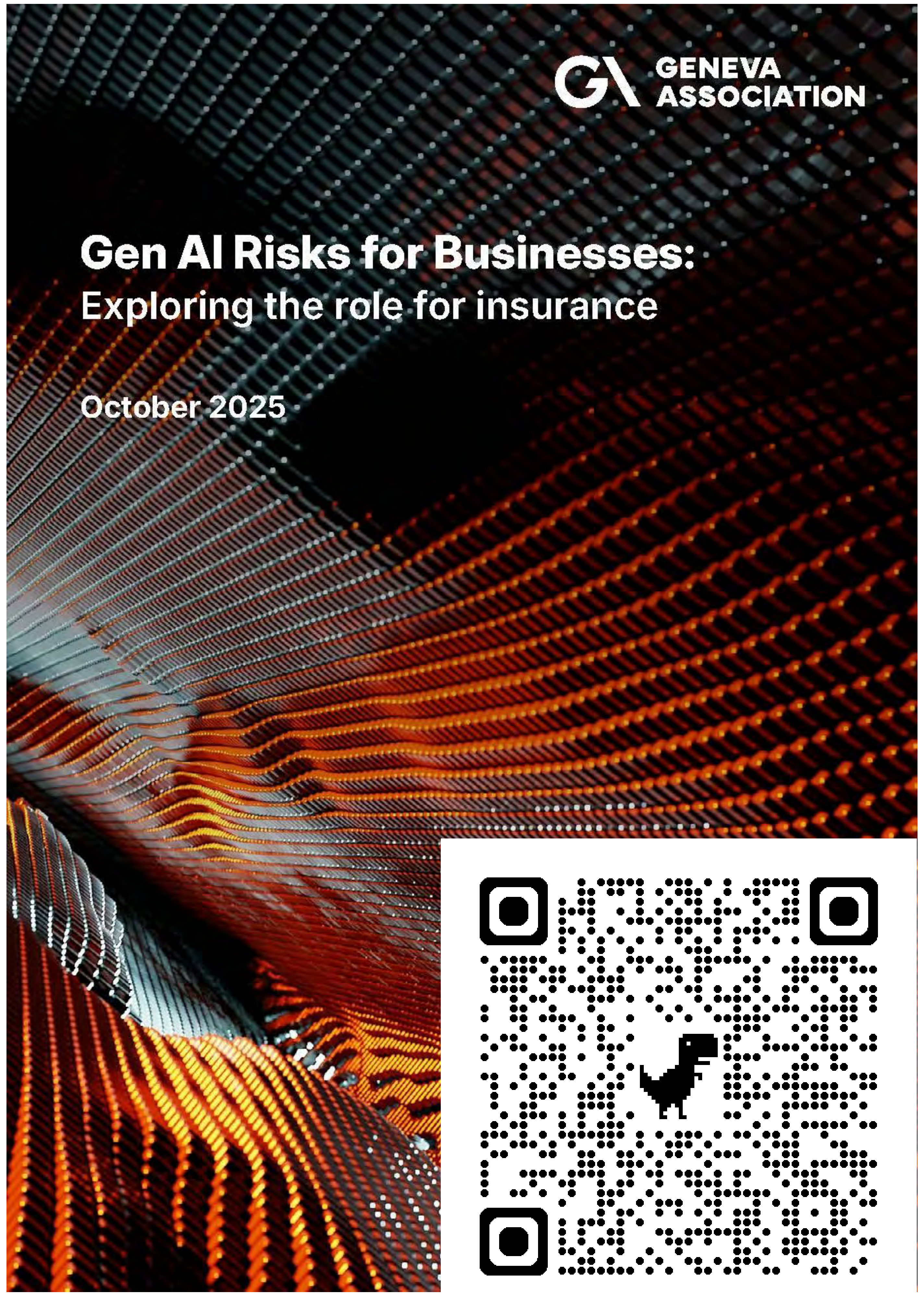
Geneva Association Gen AI and insurance report series



Report 1: Gen AI Risks for Businesses: Exploring the role for insurance (published on 2 October, 2025)

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What is Generative AI – From Prediction to Creation

Traditional AI
The Analyst

• **Function:** Analyzes data to find patterns.
• **Output:** Predictions (e.g., “Is this transaction fraudulent?”).
• **Mechanism:** Deterministic mapping of predictors.
• **Insurability:** Clearer parameters, easier to validate.

Generative AI
The Creator

• **Function:** Creates NEW content (Text, Code, Audio, Video).
• **Output:** Original artifacts.
• **Mechanism:** Probabilistic; predicts next “token” in a sequence.
• **Insurability:** ‘Black Box’ opacity makes error tracing difficult.

Two Forms of Gen AI

Insurer-Provided Tools

Specialized tools deployed directly by insurance carriers.

Examples:

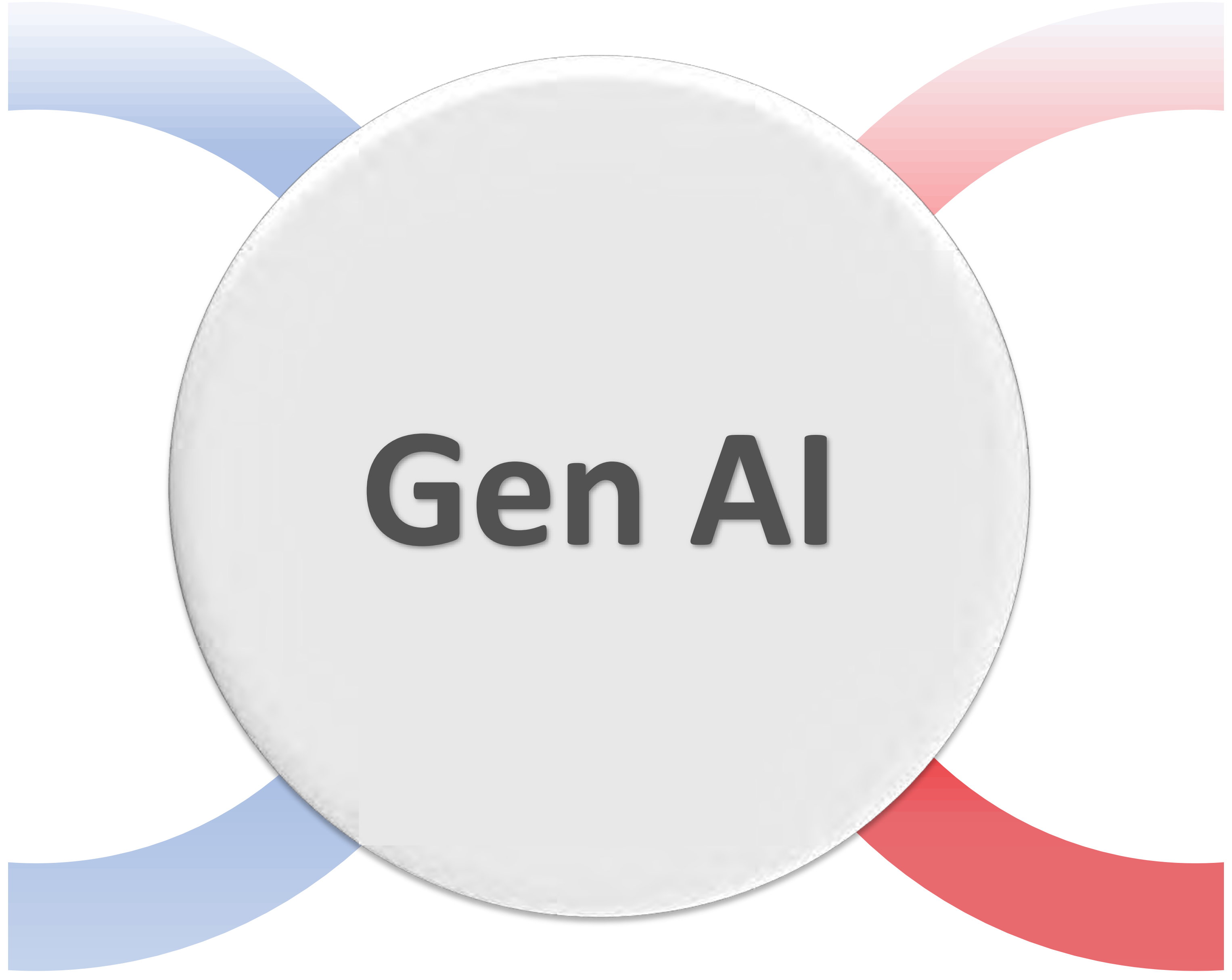
•Advanced chatbots

•Underwriting assistants

•Automated claims triage (e.g., Tokio Marine)

•Email drafting tools (e.g., Allstate)

Primary Goal:
Automation and personalized customer engagement.



Off-the-Shelf Tools

General-purpose platforms (e.g., ChatGPT, Copilot, DeepSeek) used independently by customers.

Functions:

•Analyzing insurance policies

•Comparing products

•Clarifying terms without insurer involvement

Primary Goal:
Information gathering and decision support.

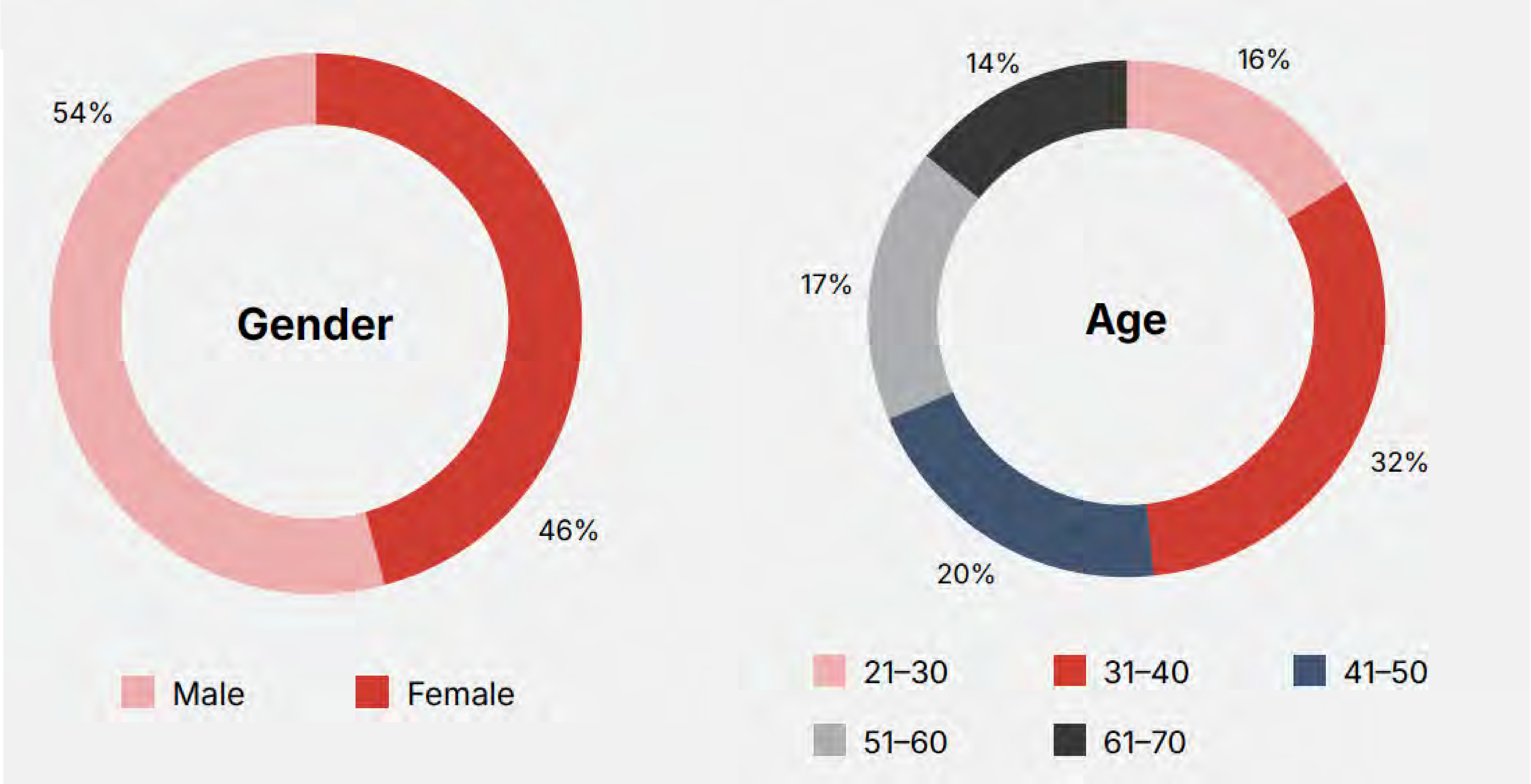
Impact Across the Customer Journey

Stages of the Insurance Journey:
- Information gathering
- Seeking advice
- Purchasing
- After-sales service
- Claims handling

Gen AI impact is strongest in:
- Advisory functions
- Claims communication
- After-sales engagement

	Gathering information	Seeking advice	Purchasing policy	After-sales service	Making a claim
Existing digital technologies (internet, mobile, social media, etc.)	High	Low → Medium	Medium	High	Medium
Additional Impact of Gen AI	High	High	Low → Medium	Medium → High	Medium → High

Customer Survey Overview

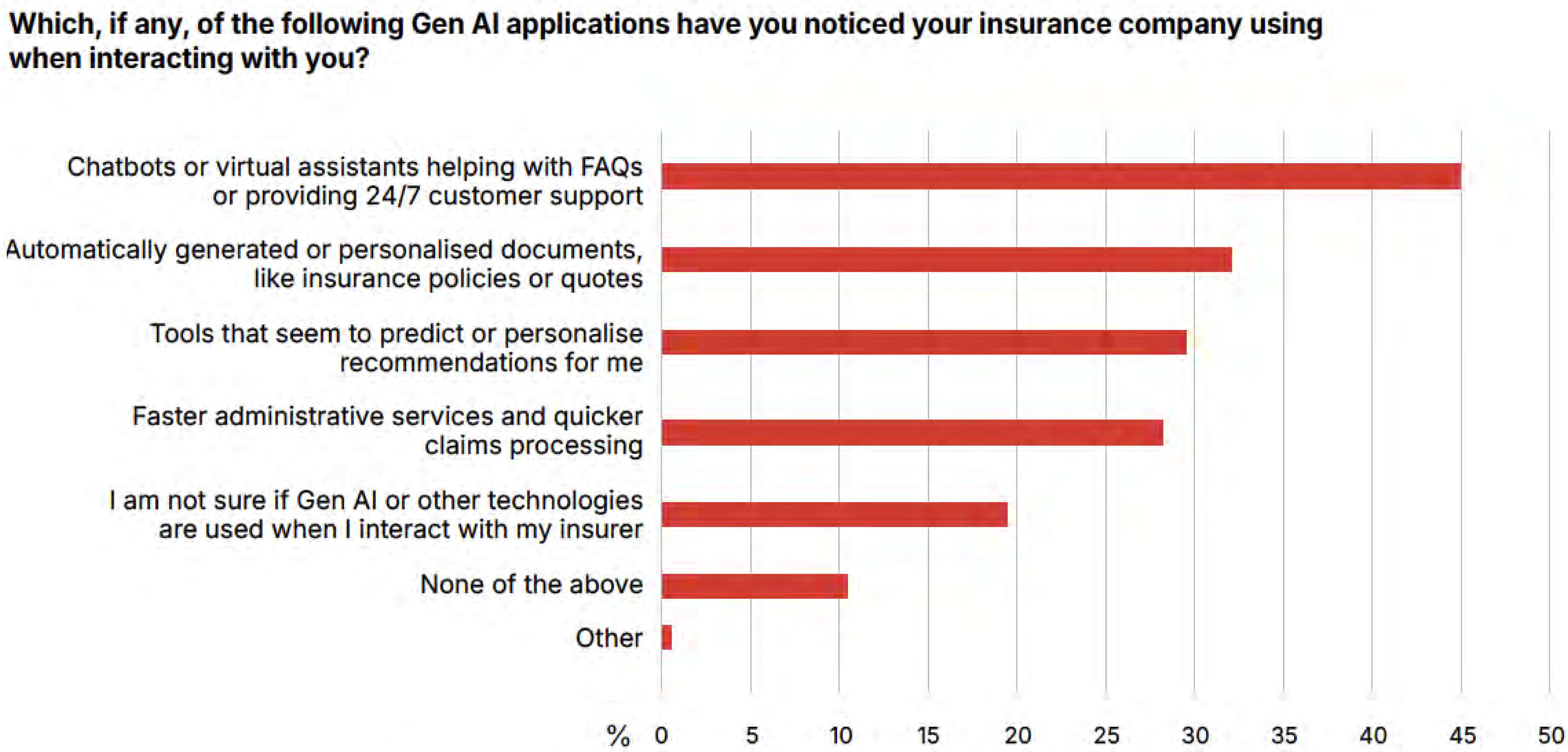


Must understand what Gen AI is.

Source: Geneva Association insurance customer survey

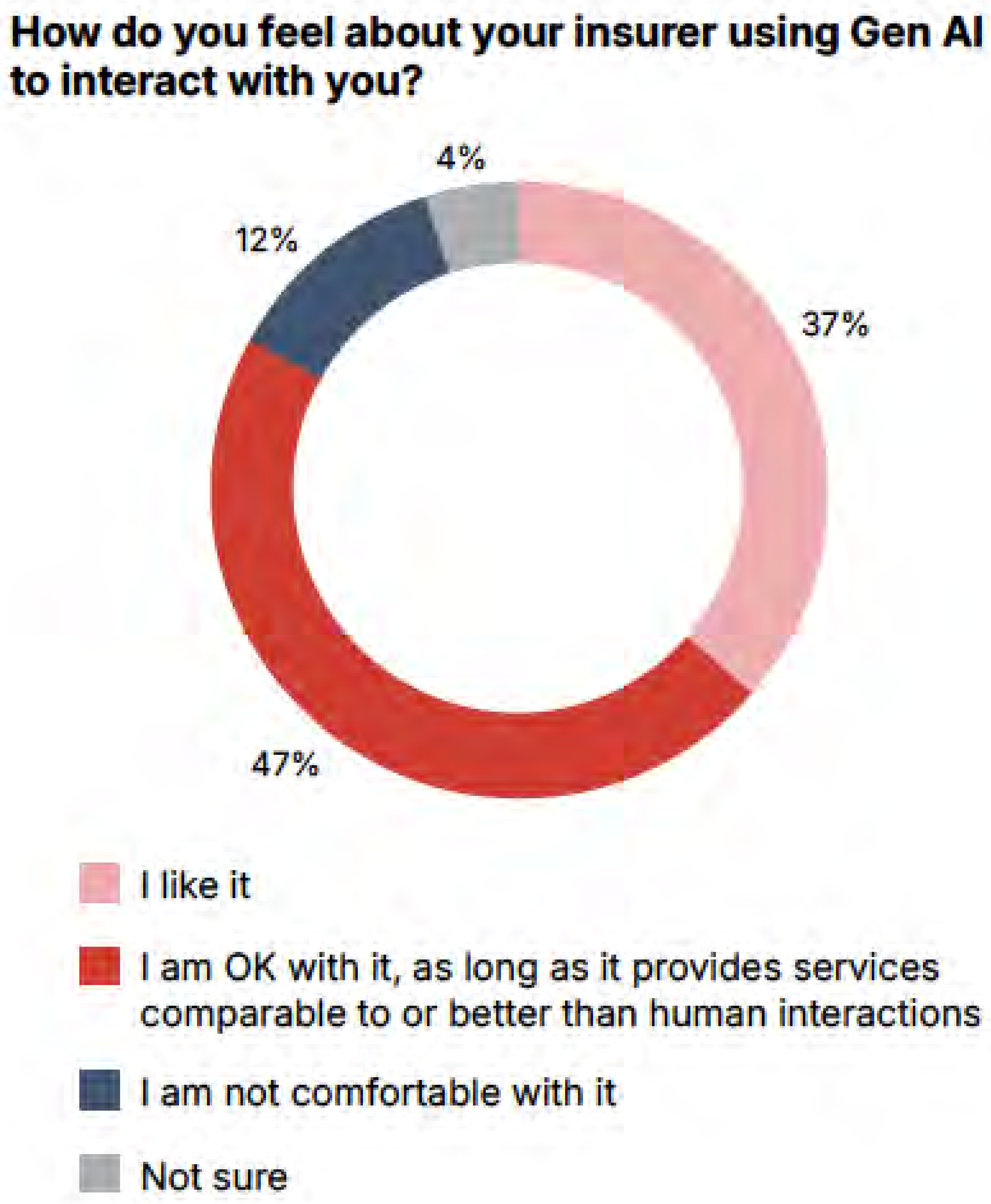
Customer Awareness of AI Use

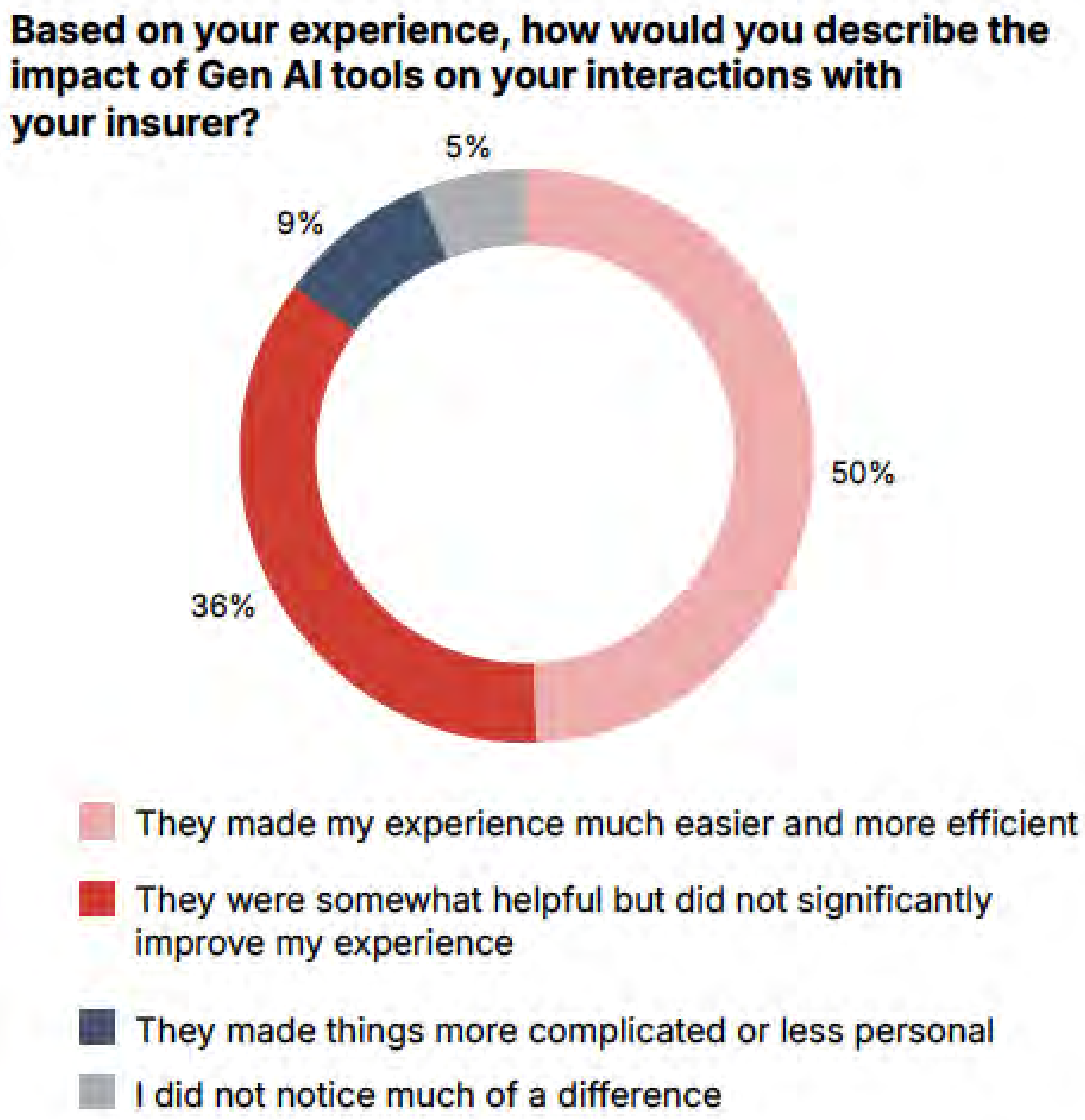
- 45% noticed chatbots / virtual assistants
- 32% noticed auto-generated documents
- 18% unsure whether AI is used



Source: Geneva Association insurance customer survey

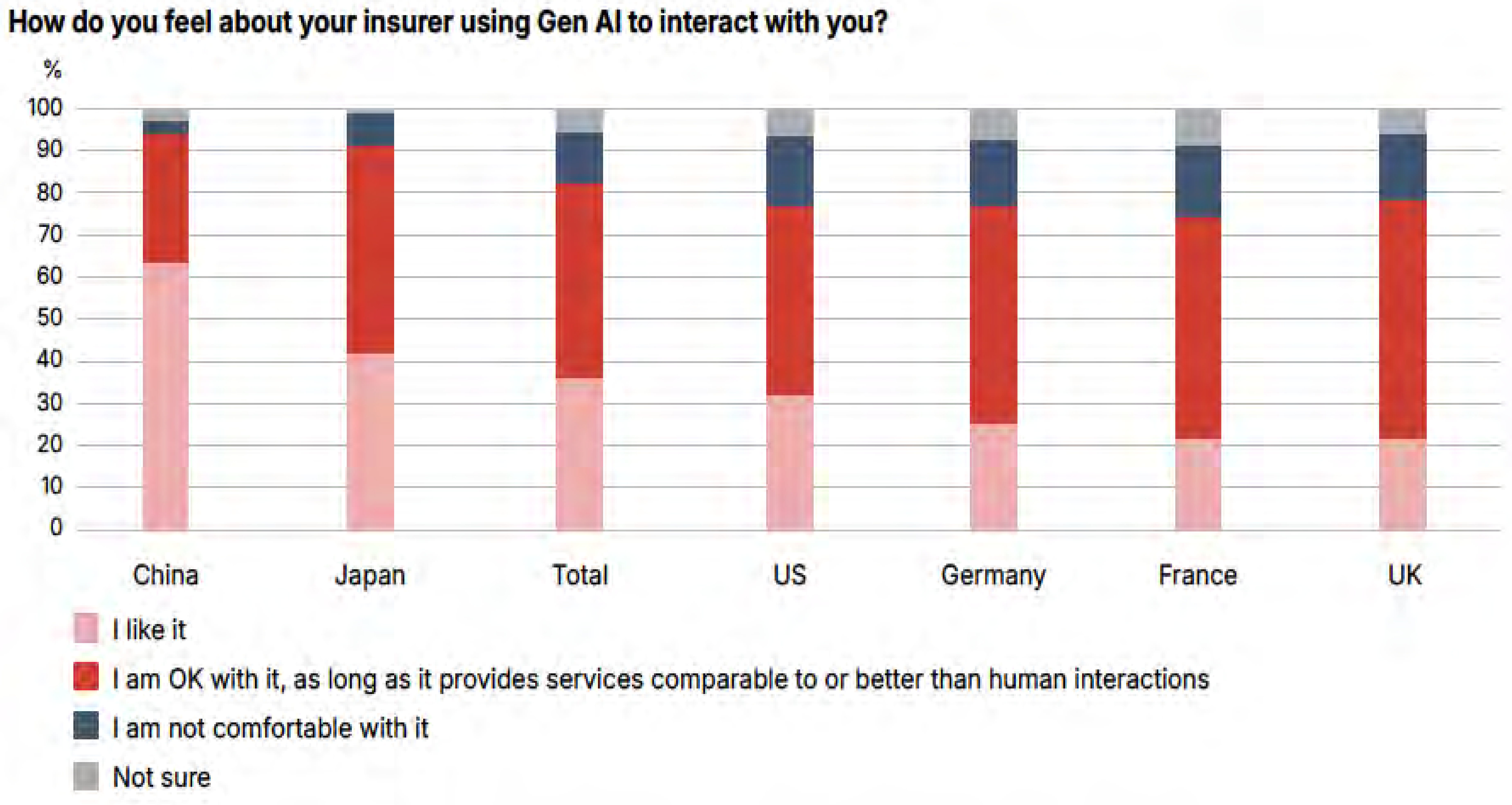
Customer Sentiment Toward Insurer provided AI:





The East-West Divide in Acceptance

Asian markets exhibit significantly higher enthusiasm compared to Western skepticism.

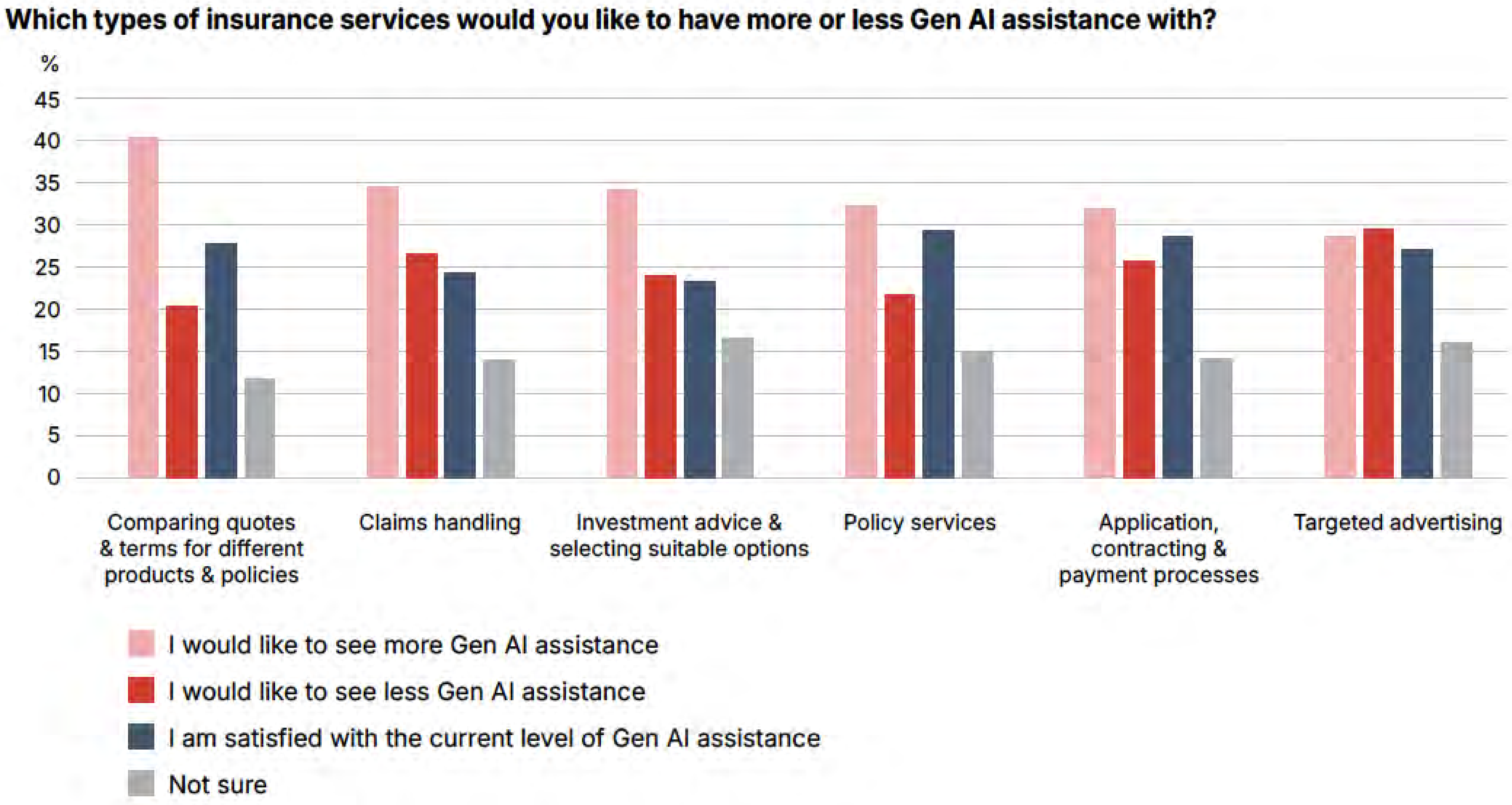


Regional Drivers

•**Asia**: High acceptance driven by digital ecosystem exposure and cultural openness.

Demand by Insurance Activity

AI is welcomed for utility, not advertisement.



Customers want **MORE** AI in:

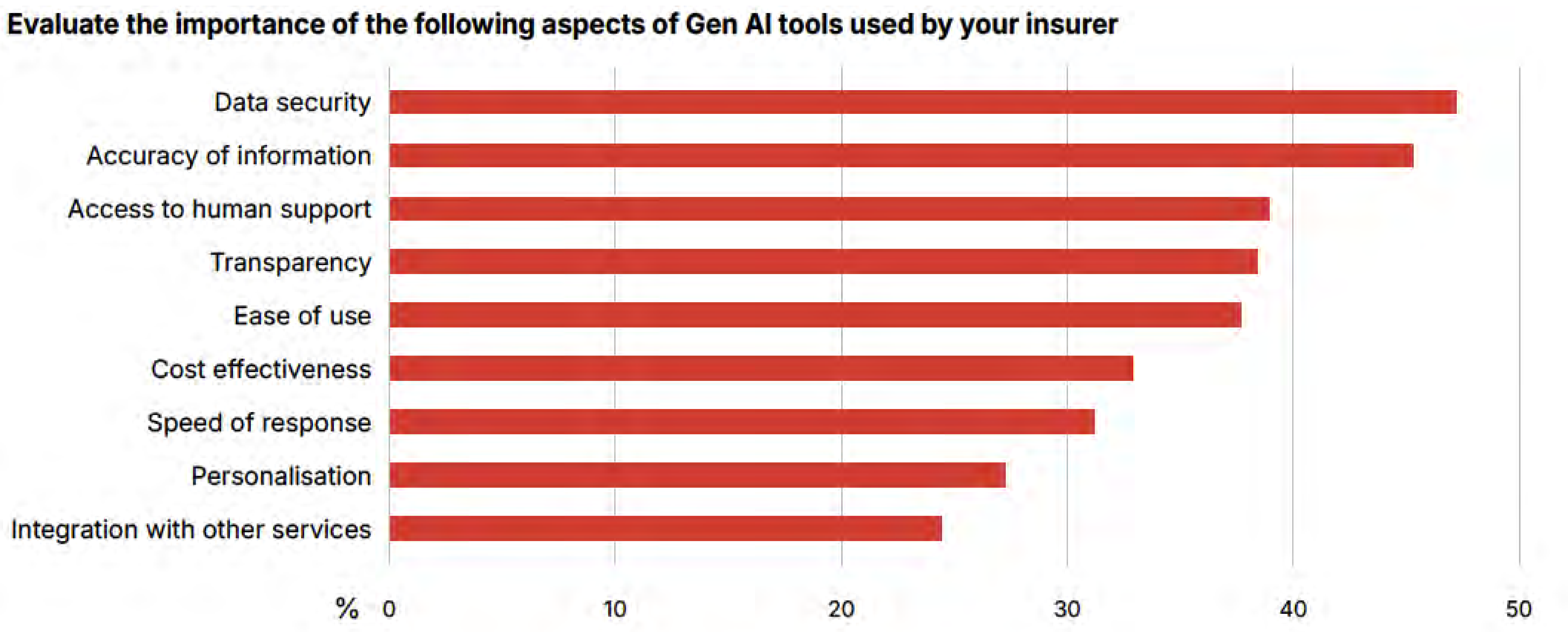
- Comparing quotes
- Claims handling
- Policy servicing

Customers want **LESS** AI in:

- Targeted advertising

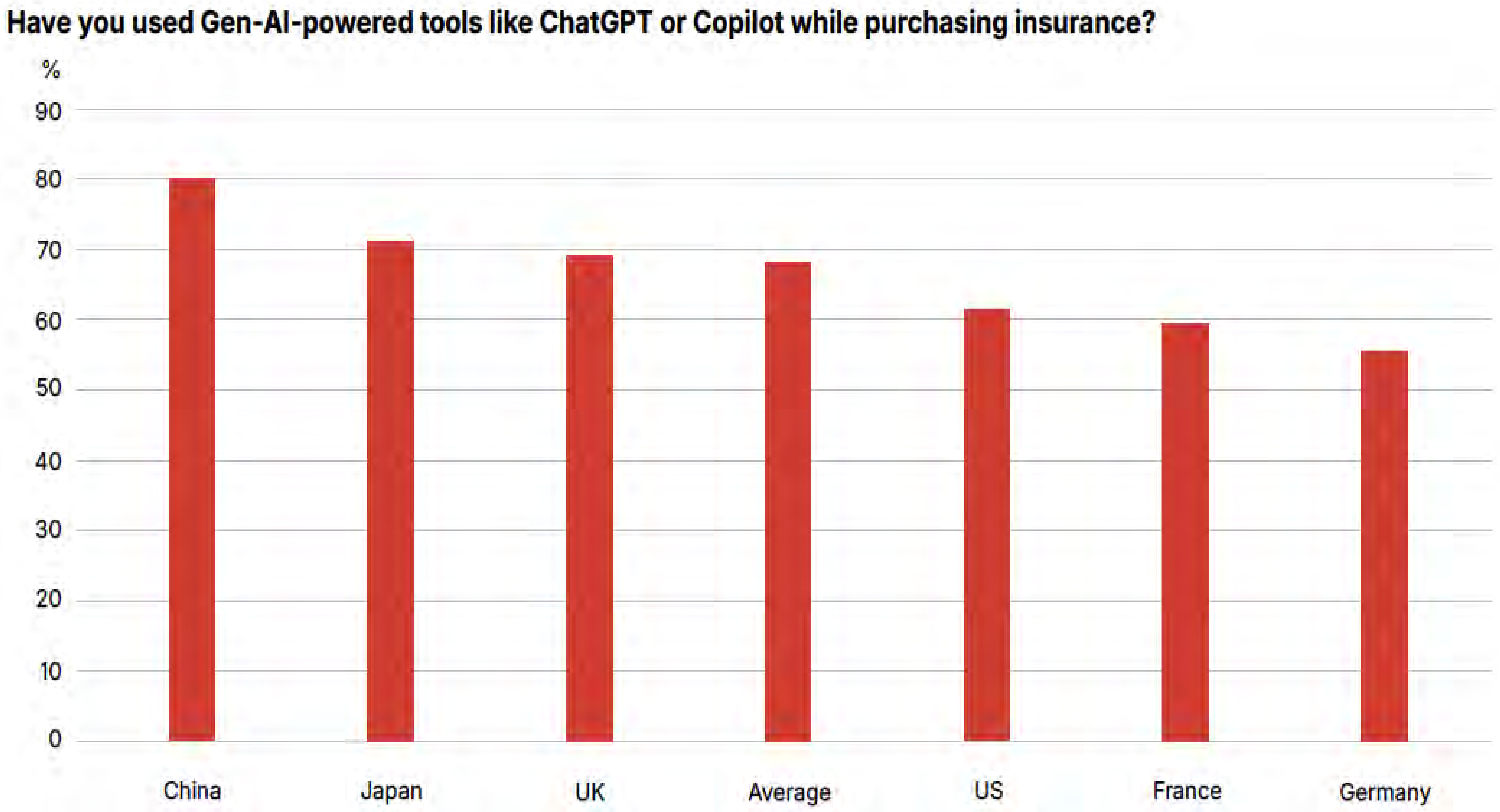
Top Customer Priorities

Trust-related factors dominate speed or cost.



The Independent Use of Gen AI

68% of respondents have used tools like ChatGPT or Copilot when purchasing insurance.



Source: Geneva Association insurance customer survey

Empowered Customers Change Market Dynamics

Off-the-shelf AI reduces:

•Information asymmetry

•Search costs

•Dependence on agents and brokers

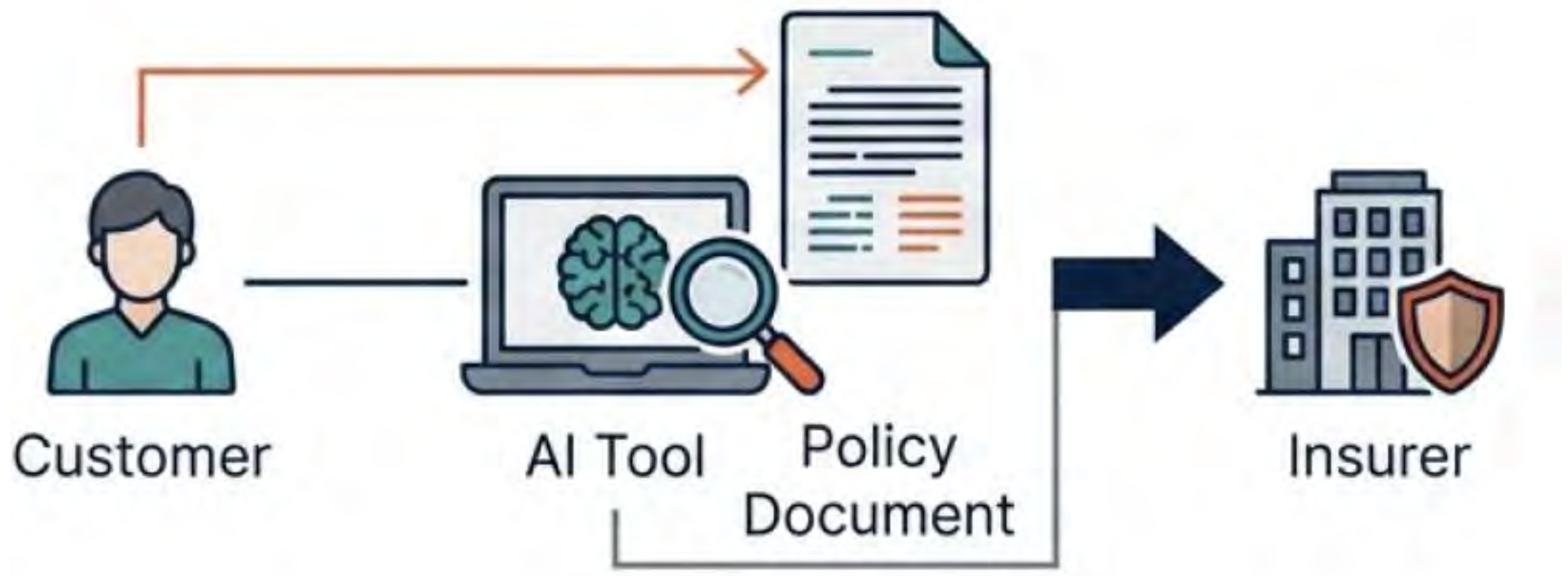
Customers become:

•Better prepared

•More analytical

•More demanding

Reducing Information Asymmetry



Customers compare products and decode complex language in real-time.

“Confusopoly” is dead. Products must be transparent to withstand AI scrutiny.

Concerns and Challenges

	Top 3 concerns	
Insurer-provided Gen AI	Lack of human touch	▪ top concern (nearly 40% respondents), more pronounced in the Europe and the U.S
	Privacy and security	▪ 35% respondents unwilling to share personal data
	Accuracy and transparency	▪ The “black box” nature and “hallucinations”
Independent use of off-the-shelf Gen AI	Quality and reliability	▪ Model bias, reliability of information and advice generated
	Privacy	▪ Misuse or leakage of sensitive personal data leaking.
	Cybersecurity risks	▪ Phishing, identity theft, and hidden vulnerabilities

Human Touch

Data Privacy

Accuracy

Transparacy

The Hallucination Risk and Mitigation Strategies

Gen AI is probabilistic, not deterministic.

Risks:

- Incorrect policy interpretation
- Fabricated exclusions
- False confirmation of coverage

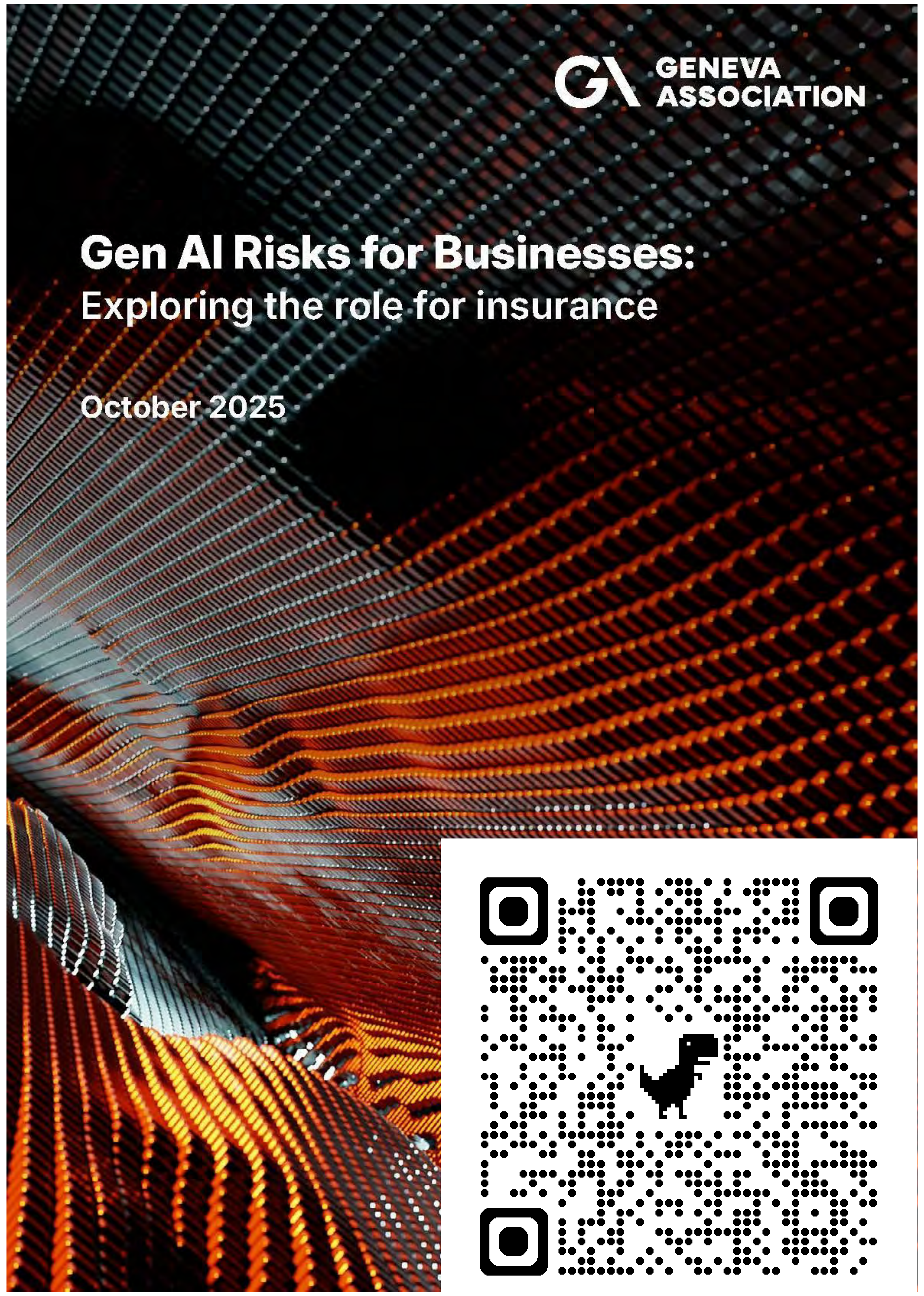
Consequences:

- Legal liability
- Regulatory penalties
- Reputational damage

RAG (Retrieval-Augmented Generation)

User Query → Retrieve Verified Doc (Policy) → Generate Answer based ONLY on Doc → Accurate Output

Geneva Association Gen AI and insurance report series



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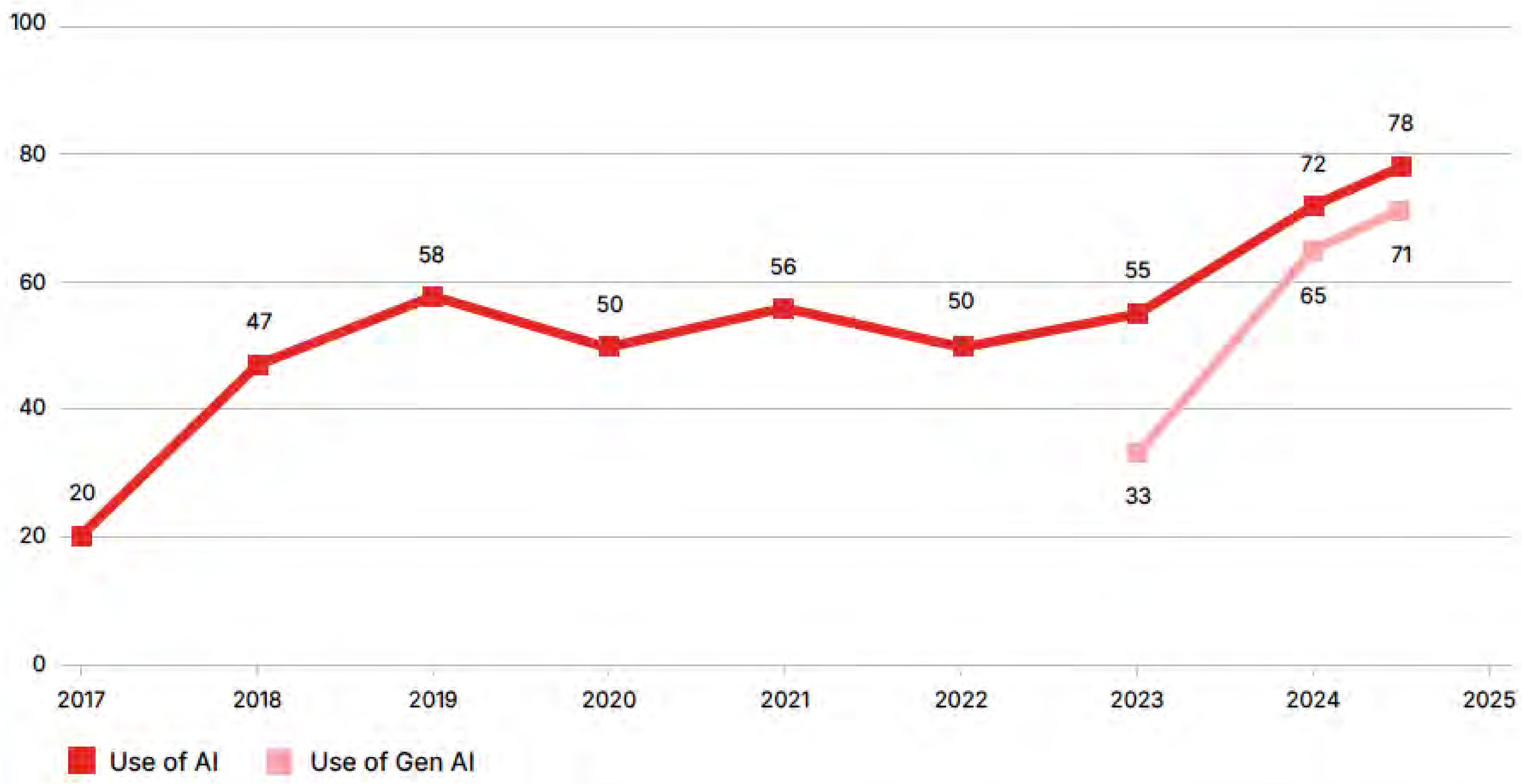
Rapid Adoption by Businesses

Adoption is accelerating globally.

•71% of firms use Gen AI in at least one function (2025)

•Up from 33% in 2023

Organisations that use AI in at least one business function, % of respondents*



* In 2017, the definition for AI use was using it in a core part of the organisation's business or at scale. In 2018–19, it was embedding at least one AI capacity in business processes or products. Since 2020, it is that the organisation has adopted AI in at least 1 function.

Source: McKinsey[8]

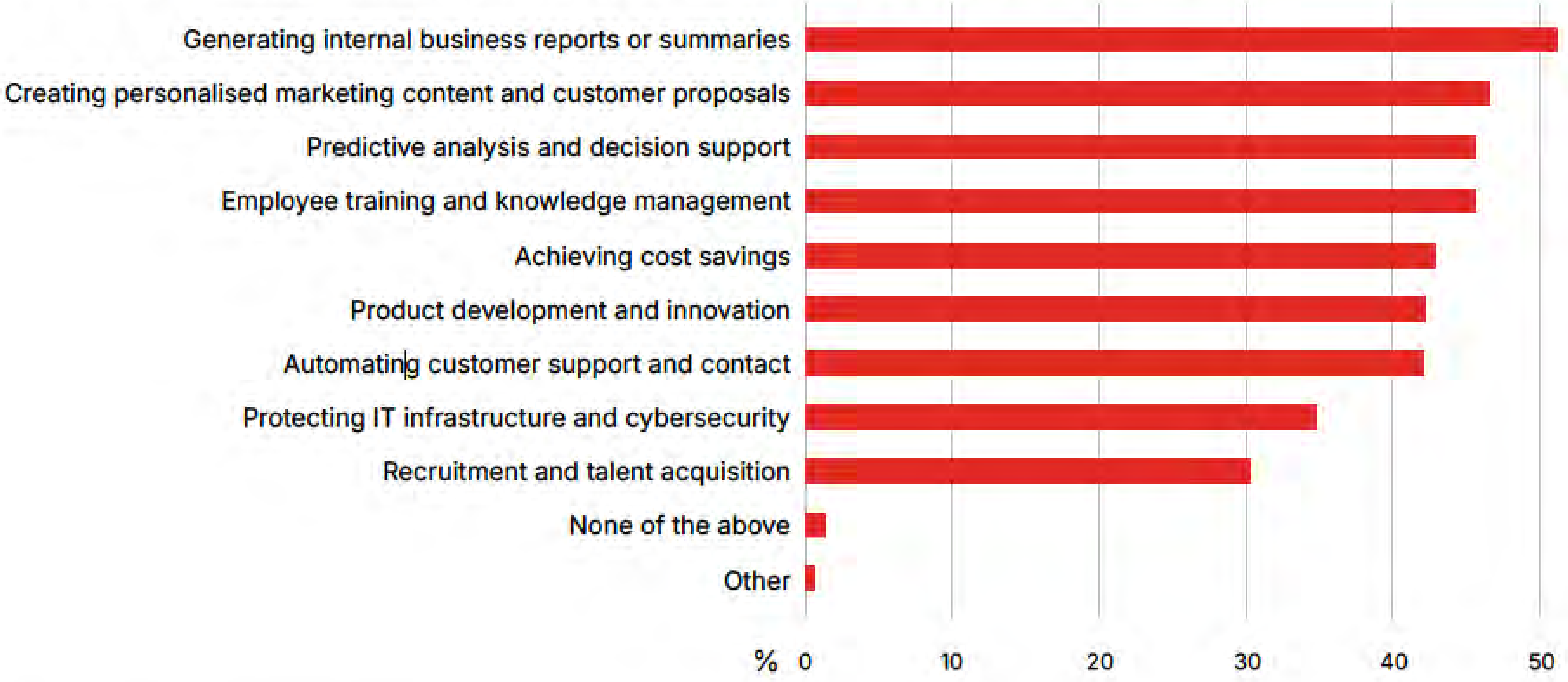
Seven risk categories identified for Gen AI

- Operational, privacy & cybersecurity, ethical, regulatory, reputational, workforce, ESG

	Risk Category	Specific Risk
First-party operational risk	Operational	Algorithmic Errors; Stability; Reliability Black-Box Issues Malicious Attack
	Cybersecurity & Privacy	AI-driven Cyberattacks Data Privacy Violations
	Reputational & Market	Customer Trust and Brand Image Dependency & Competitive Risk
	Workforce Challenges	Job Displacement AI Skill Requirements
First-party operational risk +Third-party product risk	Regulatory & Compliance	Evolving AI Regulations Accountability and Liability
	Bias & Ethical Concerns	Discrimination and Bias Ethical Decision-Making
	ESG	Environmental and Energy

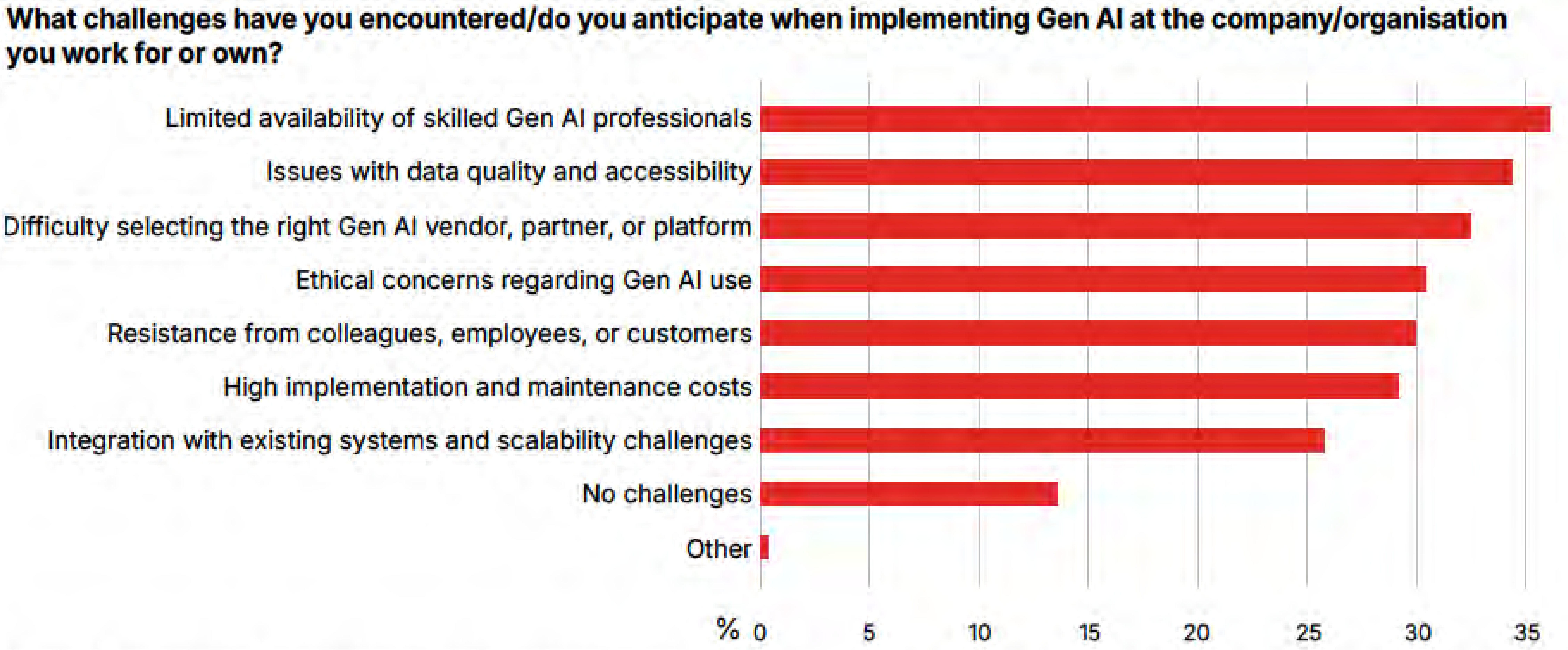
How Firms Use Gen AI

For what purposes do you use Gen AI at the company/organisation you work for or own?



Source: Geneva Association business insurance customer survey

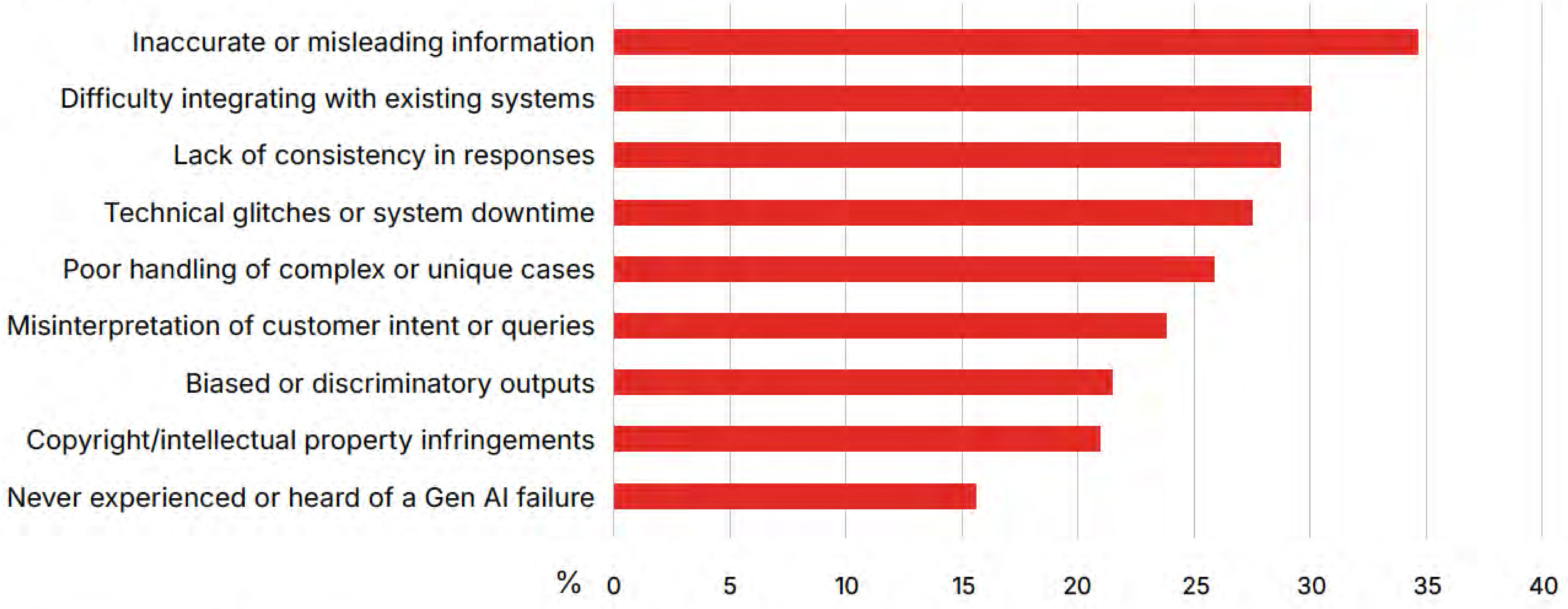
Implementation Challenges



Source: Geneva Association business insurance customer survey

Failures & Incidents

What type(s) of failures or issues have you experienced or heard about when using Gen AI in the company/organisation you work for or own?

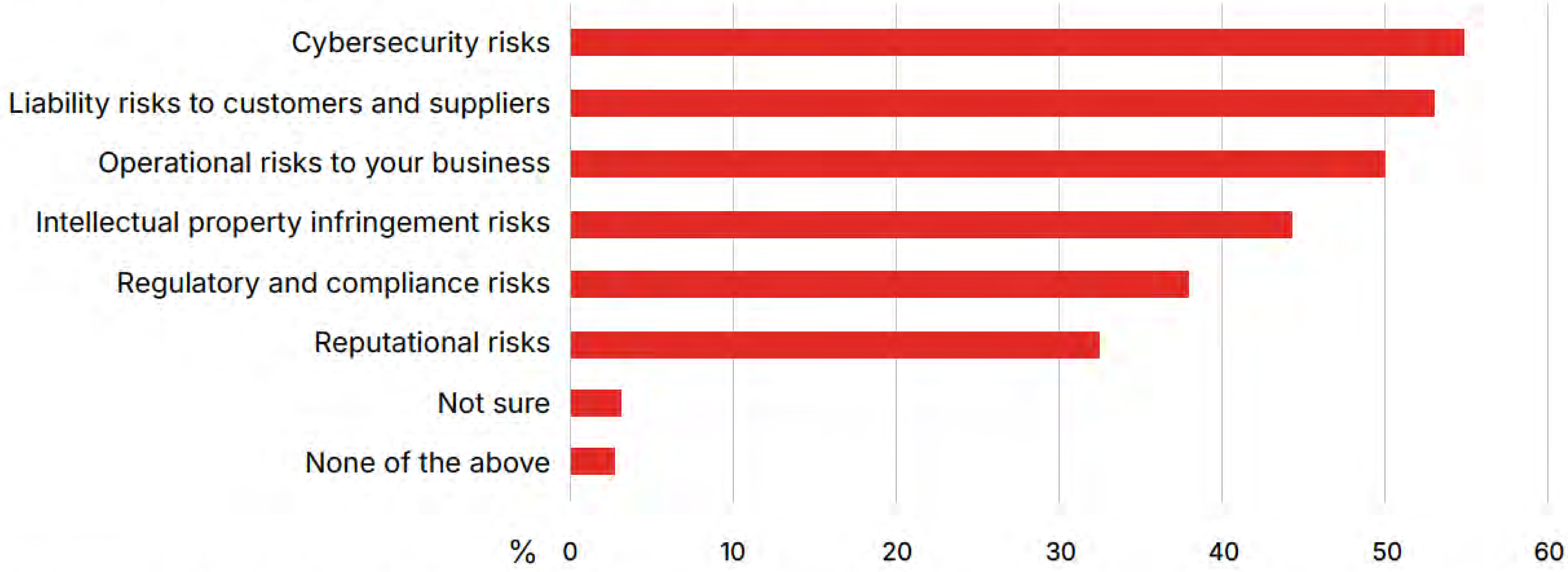


Source: Geneva Association business insurance customer survey

Demand for Gen AI Insurance

FIGURE 7: GEN AI RISKS BUSINESSES WANT TO INSURE

What Gen-AI-related risks do you want covered by your insurance?



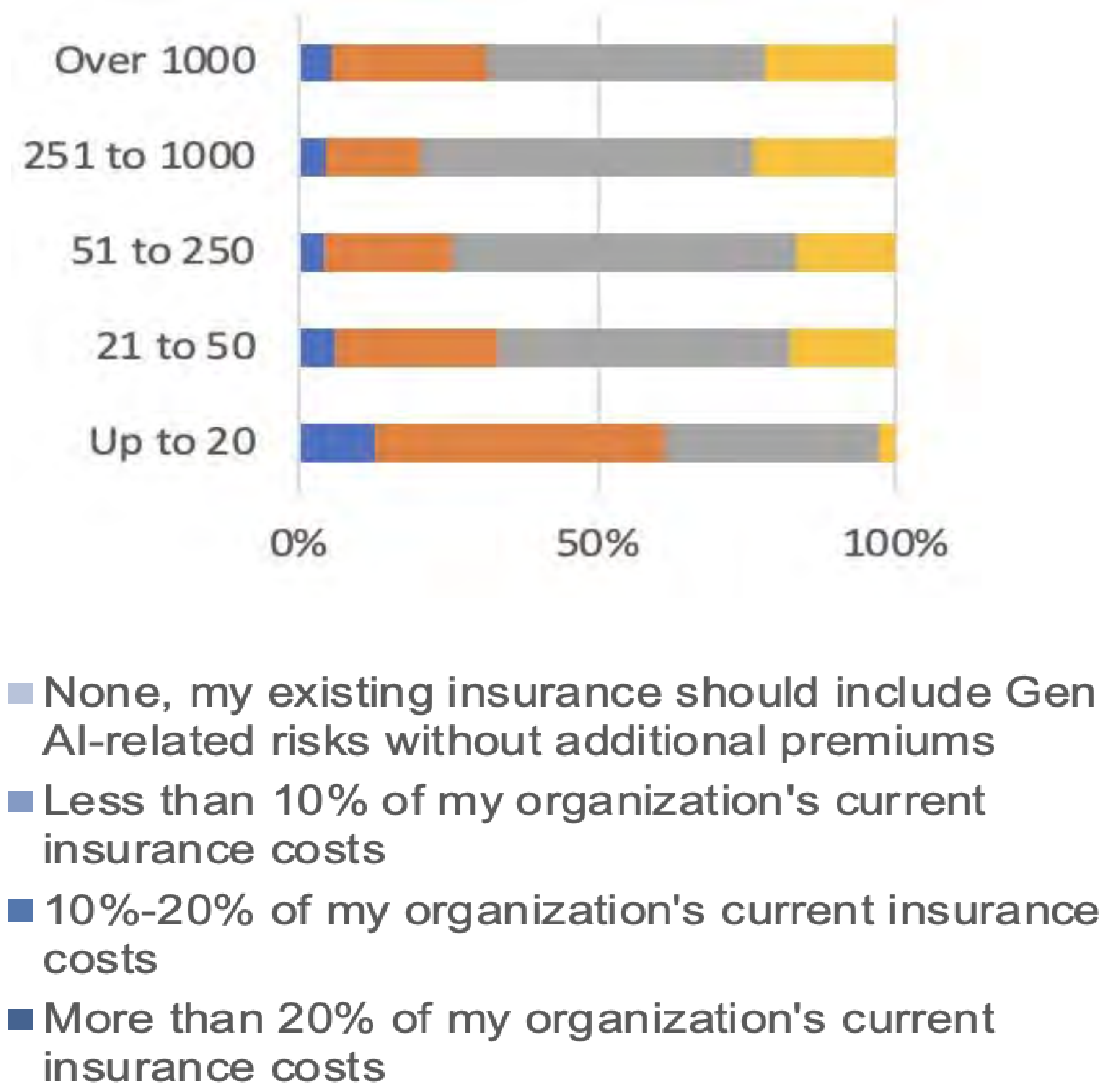
Source: Geneva Association business insurance customer survey

Demand for Gen AI Insurance

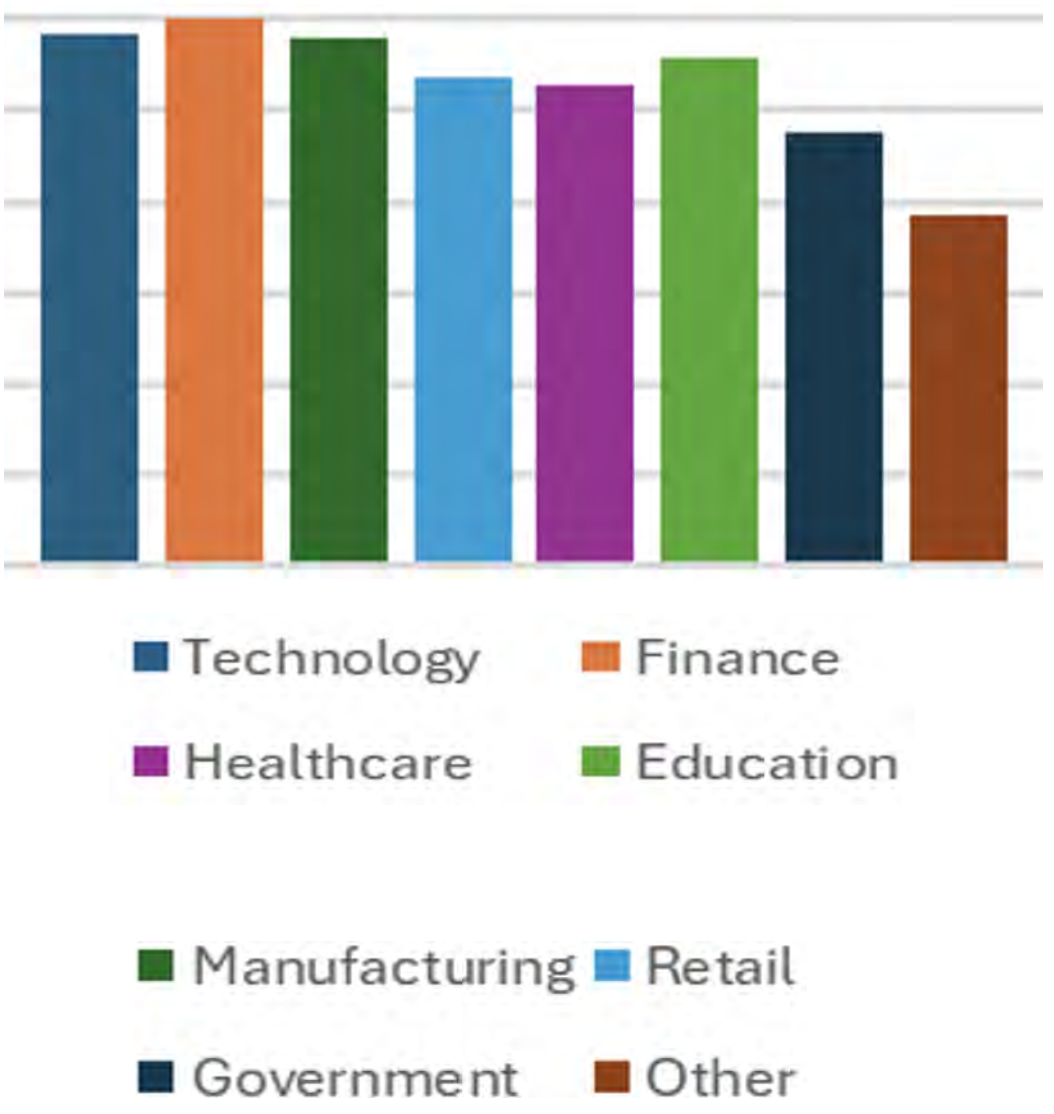
- Demand is strongest in the technology and finance sectors, among medium-to-large firms, and in markets with high Gen AI adoption
- Firms with high Gen AI exposure and severe past failures show higher insurance demand, suggesting potential adverse selection

⦿ From whom is Gen AI insurance in high demand

Business size

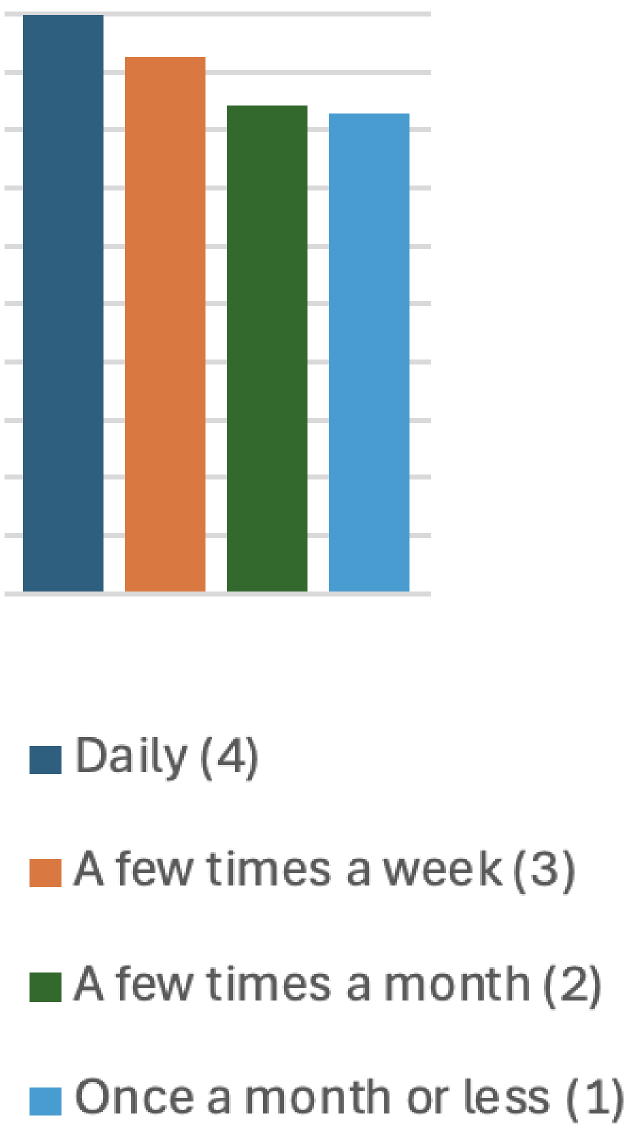


Industries

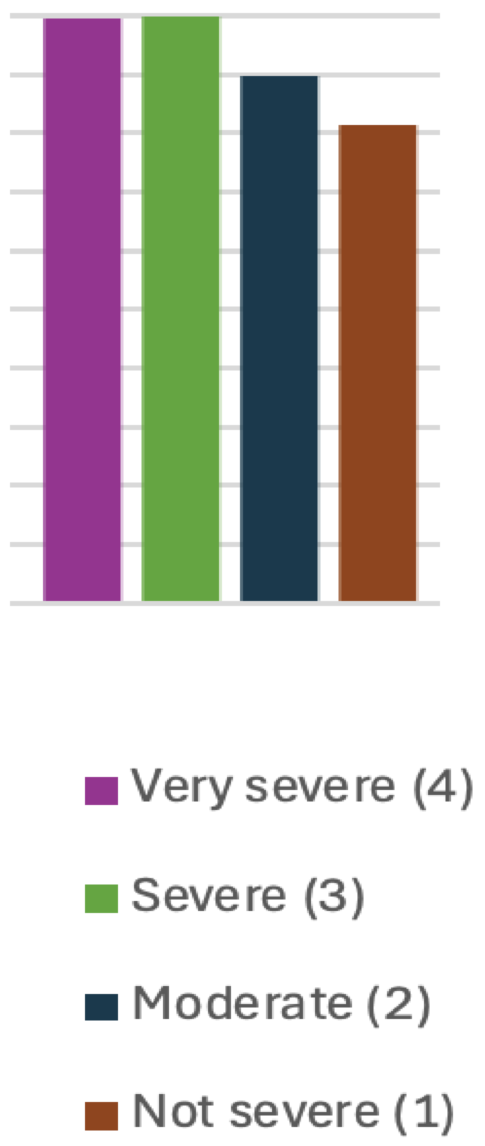


Across markets

Risk exposure



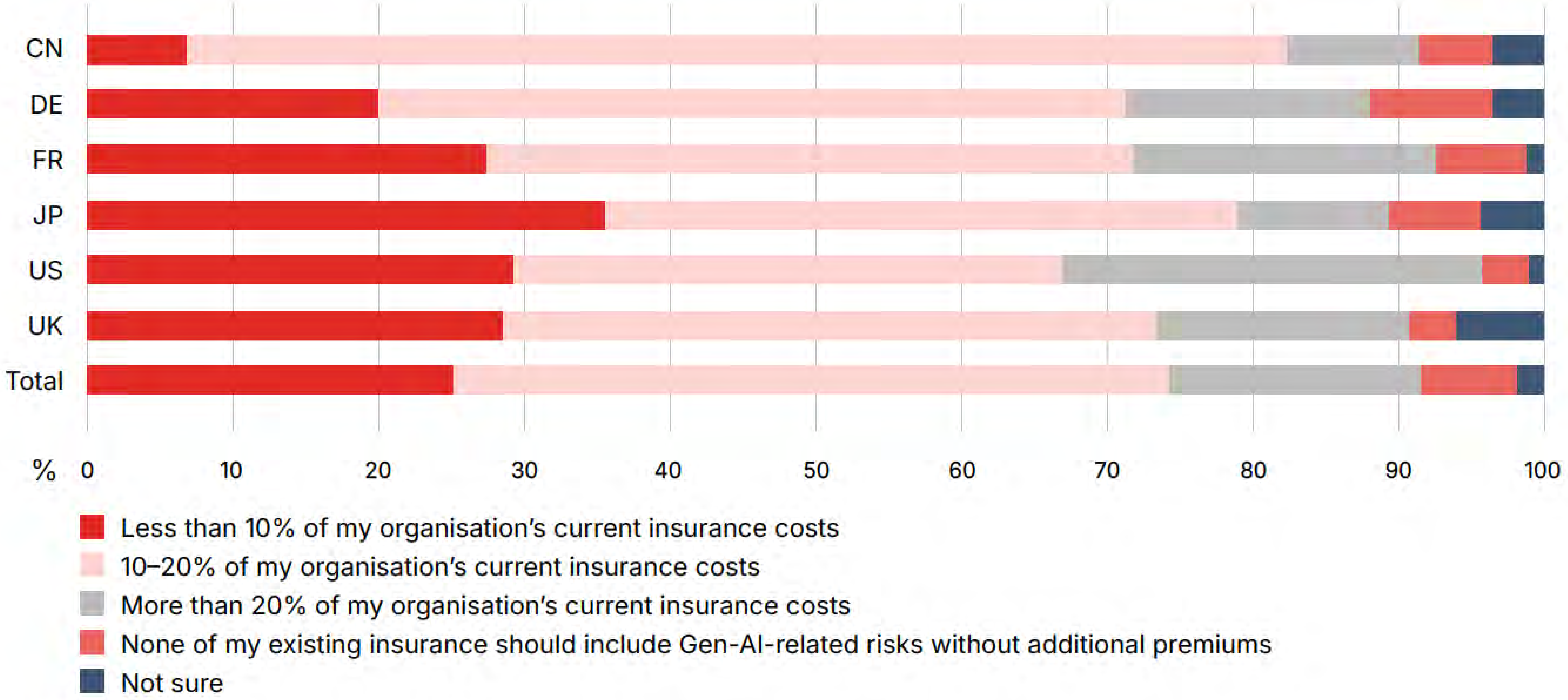
Failure severity



Willingness to Pay

FIGURE 8: WILLINGNESS TO PAY FOR GEN AI INSURANCE

How much extra would you be willing to pay for Gen-AI-related coverage?



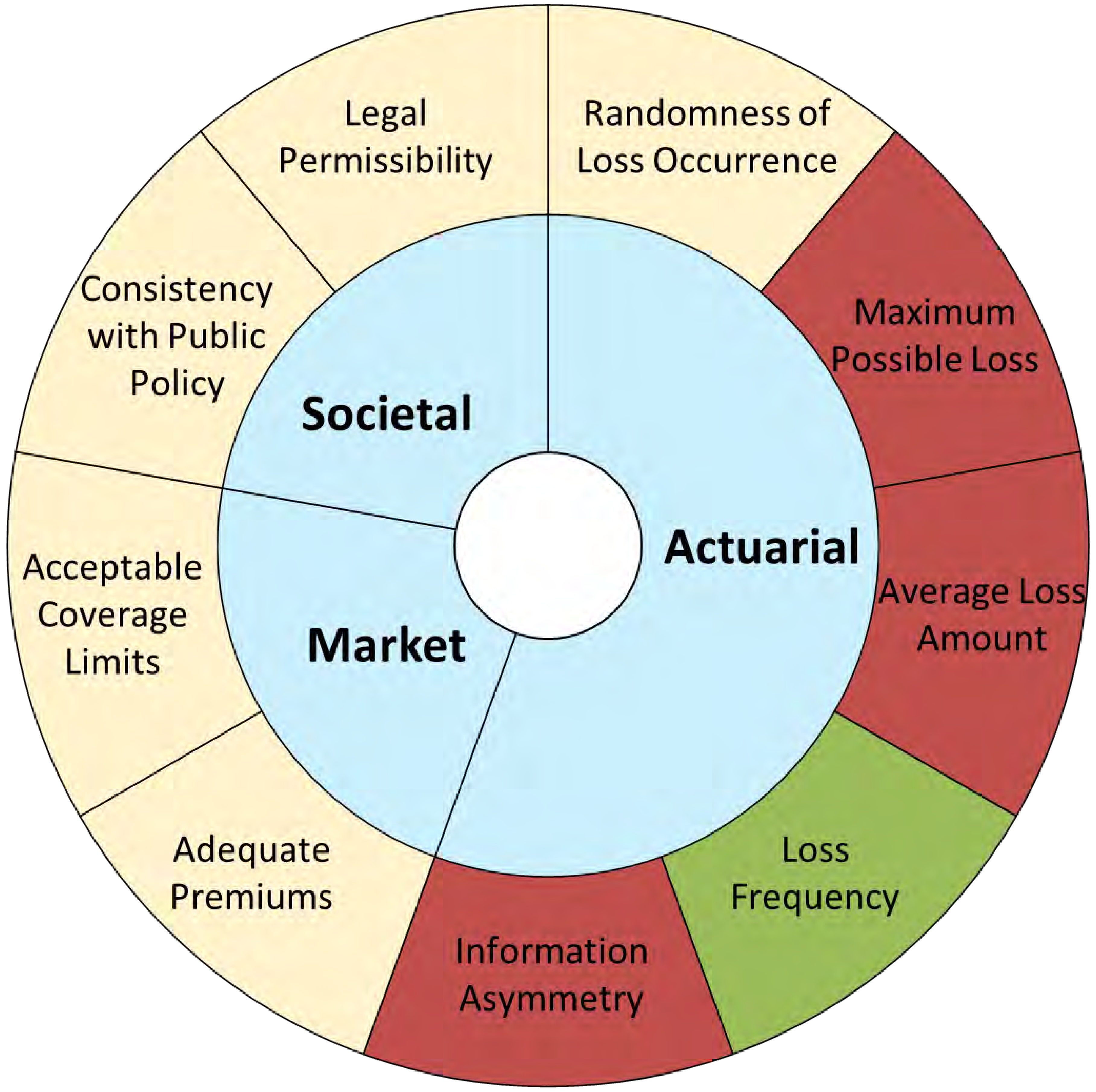
Source: Geneva Association business insurance customer survey

Supply of Gen-AI-related insurance

Insurability of Gen-AI-related risks

- Critical challenges for Gen AI:
    - Maximum possible loss
    - Average loss amount
    - Information asymmetry

- Mirrors the early evolution of cyber insurance



Source: Geneva Association

Emerging insurance solutions

- Gen-AI-related risks and associated coverage are still at an early stage but are expected to expand
- Effective Gen AI risk management requires a broad toolkit – a balanced approach combining risk avoidance, mitigation, retention, and transfer

Type of coverage	Description
Cyber insurance	Covers losses due to enhanced vulnerability of IT systems, as businesses and attackers use Gen AI tools, including data breaches, hacking, or model manipulation.
Professional liability (E&O)	Protects against claims arising from errors in Gen AI outputs, like the generation of misleading or harmful information.
Directors' & officers' liability	Protects directors and officers from legal action due to Gen-AI-related decisions or oversight failures.
Intellectual property	Protects against claims related to Gen AI's use of copyrighted or patented materials without permission.
Product liability	Covers claims due to harm caused by Gen AI outputs (e.g. misinformation, discriminatory content) or failure to perform as expected.
Dedicated, standalone AI insurance	Comprehensive, standalone coverage bundling multiple Gen-AI-specific exposures into a single policy.

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Cyber Risk Pricing: Current Challenges and the AI-Driven Future

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June 2026

Cyber Incident and Cost Trends (2025)

- **Incident Volume (2025 YTD):**
  - ITRC reports **2,563 incidents** in first 9 months.
  - Impacting approx. **202 million** victim notices [1].
- **Financial Impact by Region:**
  - Global Average Cost: **$4.44 million** (decreased 9%).
  - **United States Average: $10.22 million** (Record High) [2].
- **Cost Disparity by Size (NetDiligence Study) [3]:**

Metric	**SME**	**Large Enterprise**
Avg. Incident Cost	$264,000	$10.3 Million
Business Interruption	$1.8 Million	$36.1 Million

Sources: [1] ITRC Q3 2025 Analysis, [2] IBM Cost of a Data Breach Report 2025, [3] NetDiligence Cyber Claims Study 2025

Cyber Insurance Market Overview

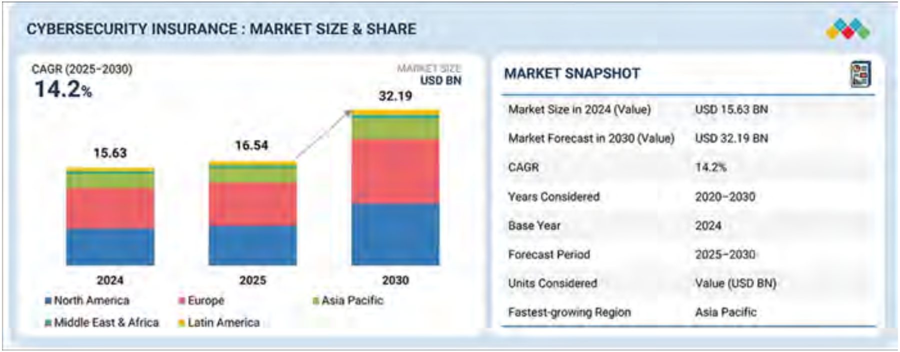


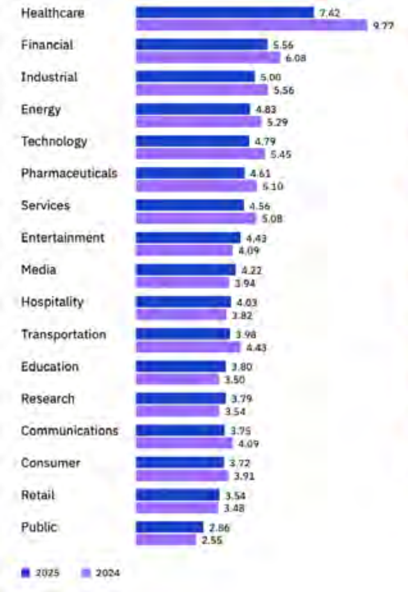
Figure: Cyber insurance market. Source: MarketsandMarkets.

NACIS 2025: Global premiums reached nearly **$15 billion**. North America: 64.9%

Top 20 companies in US

2024 Rank	2023 Rank	Group Name	Direct Written Premium	Loss Ratio with DCC	Market Share	Cumulative Market Share
1	1	Chubb Lt Grp.	$560,634,065	36.06%	7.92%	7.92%
2	4	St Paul Travelers Grp.	$535,426,655	53.97%	7.56%	15.48%
3	3	Fairfax Financial	$360,580,980	39.66%	5.09%	20.58%
4	5	Tokio Marine Holding Inc.	$355,982,823	43.47%	5.03%	25.60%
5	2	AXA Ins. Grp.	$340, 448,442	36.03%	4.81%	30.41%
6	7	Arch Ins. Grp.	$285,033,459	41.67%	4.03%	34.44%
7	32	At Bay Specialty Ins. Grp.	$280,601,661	55.78%	3.96%	38.40%
8	8	American Intrnl. Grp.	$276,564,105	49.26%	3.91%	42.31%
9	9	Sompo Grp.	$262,732,079	57.84%	3.71%	46.02%
10	10	Starr Grp.	$255,087,002	96.26%	3.60%	49.62%
11	11	CNA Ins. Grp.	$240,279,671	74.84%	3.39%	53.02%
12	14	AXIS Capital Grp.	$204,589,956	26.73%	2.89%	55.91%
13	18	AmTrust Financial Serv. Gr.	$202,476,467	48.33%	2.86%	58.77%
14	6	Berkshire Hathaway	$187,578,016	85.72%	2.65%	61.42%
15	16	Hartford Fire & Cas Grp.	$185,549,193	11.53%	2.62%	64.04%
16	19	Beazley Grp.	$184,854,545	9.24%	2.61%	66.65%
17	28	QBE Ins. Grp. Ltd.	$184,062,830	89.31%	2.60%	69.25%
18	15	Liberty Mut. Grp.	$169,793,294	70.72%	2.40%	71.65%
19	13	Zurich Ins. Grp.	$168,205,234	78.31%	2.38%	74.03%
20	17	Ascot Ins. US Grp.	$156,769,170	45.19%	2.21%	76.24%

Figure: DWP and loss ratios for the top 20 insurer groups.



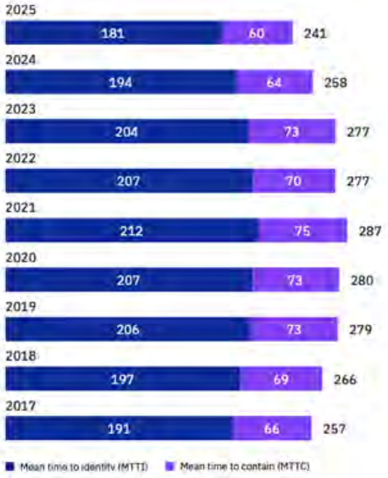
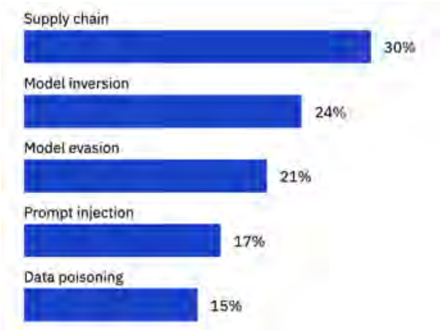
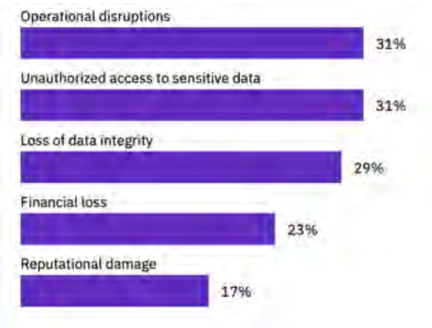


Figure: Healthcare is still the costliest sector, while response times are improving

AI Risk?



(a) Incidents involving AI models



(b) Impacts of incidents on authorized AI

Figure: AI exposure is not confined to one deployment mode, which complicates cyber underwriting and vendor-risk assessment. Future cyber pricing may need separate loadings for AI governance, vendor dependence, and internal model deployment choices. Examples: 2024–Chatbot misinformation: Air Canada; 2023–Confidential data leakage: Samsung and ChatGPT.

Why is cyber risk pricing uniquely hard?

Fast-moving threats

Attack patterns, tools, and exposures evolve faster than annual underwriting cycles.

Interdependence and accumulation

Shared cloud, software, vendors, and service providers can turn one event into many correlated claims.

Sparse and shifting loss data

Claims histories are limited, policy terms change over time, and observed losses reflect a changing market.

Heavy-tailed losses

Rare but severe incidents dominate capital requirements and pricing, yet are the hardest to calibrate.

Cyber pricing is difficult because insurers must price evolving threats with limited data while accounting for portfolio-wide accumulation from shared vendors, cloud platforms, and software dependencies.

How cyber risk is priced today

In practice, cyber pricing is a triangulation problem.

Insurers combine exposure data, security signals, scenarios, and underwriter judgment.

Exposure view

Uses size, sector, revenue, records, vendors, and core controls.

Limitation:often proxy-heavy and backward-looking.

Security view

Uses scans, questionnaires, security ratings, and control evidence.

Limitation:may miss internal context and control quality.

Scenario view

Stress-tests ransomware, outage, breach, cloud, and vendor events.

Limitation:depends on assumptions and expert judgment.

Cyber premiums are built from multiple noisy signals and adjusted for limits, exclusions, accumulation, and portfolio appetite.

How cyber risk is priced in practice

Evidence from public rate filings: cyber pricing is usually implemented through rating algorithms, rather than one universal actuarial model.

Pricing	Stylized formula	Interpretation
Flat rate	$P_c = \frac{q_c s_c}{1-\ell}$	Fixed premium for coverage c, based on assumed frequency q_c, average severity s_c, and loading ratio ℓ.
Hazard group	$P_i = P_{h(i),c,L,R}$	Premium selected from a filed table by hazard group $h(i)$, coverage c, limit L, and retention R.
Base rate	$P_i^{\text{base}} = BP_i F_{\text{limit}} F_{\text{retention}} F_{\text{industry}}$	Exposure-based base premium adjusted by limit, retention, and industry factors.
Risk modifiers	$P_i = P_i^{\text{base}} \prod_{k=1}^{K} F_{ik}$	Claims history, security controls, governance, policy terms, and sublimits enter as rating modifiers.

Public SERFF-style filings suggest cyber pricing is often table-driven, with increasing refinement from flat rates to exposure-based formulas with underwriting modifiers. These are representative rating structures; actual carrier models are proprietary and vary by insurer.

Unifying representation of filed rating algorithms

$$P_i^* = \sum_{j \in \mathcal{C}} \left[BP_{ij} \prod_{k=1}^{K_j} F_{ijk} \right] \times F_i^{\text{discount}} \times F_i^{\text{policy term}}.$$

$$P_i = \max\{P_i^*,\ P_i^{\min}\} + S_i.$$

Component	**Meaning**
$j \in \mathcal{C}$	Coverage modules, such as third-party liability, first-party incident response, cyber crime, system interruption, or extortion.
BP_{ij}	Base premium for firm i and coverage module j.
F_{ijk}	Rating factors such as limit, retention, industry, claims history, data classification, security controls, governance, sublimits, or retroactive date.
$P_i^{\min}$	Minimum premium floor, applied after the calculated premium is obtained.
S_i	Explicit surcharge or fee, if separately applied.

How scenario models affect firm-level pricing

Scenario models are usually portfolio-level tools used to assess accumulation, capital, reinsurance, and capacity.

$$P_i = P_i^{\text{account}} + \lambda_i^{\text{acc}}, \qquad \lambda_i^{\text{acc}} \propto \rho(L_{\text{port}} + L_i) - \rho(L_{\text{port}}).$$

In practice, the scenario load may appear as:

higher premium or lower limit or higher retention or sublimits/exclusions.

Portfolio finding	Possible underwriting response
High cloud/vendor concentration	Higher accumulation load, lower offered limit, or stricter vendor exclusions.
High ransomware aggregation	Higher retention, tighter ransomware sublimit, or stronger control requirements.
High business interruption tail	Higher BI rate, waiting period, sublimit, or coinsurance adjustment.
High reinsurance/capital cost	Higher technical price, capacity reduction, or portfolio rebalancing.
Diversifying account	Smaller accumulation load or more favorable capacity.

Scenario pricing asks whether this firm increases the insurer's exposure to shared cloud providers, software vendors, MSPs, ransomware waves, or other systemic cyber events.

Where current cyber pricing approaches fall short

Dynamic threat environment
Point-in-time assessments decay quickly as attackers, tools, vulnerabilities, and exposures evolve.

Systemic accumulation risk
Cloud, software, vendor, and managed service provider dependencies can turn one event into many correlated claims.

Extreme-loss tails
Rare but severe cyber events matter most for capital, reinsurance, and pricing discipline.

Sparse data and reporting bias
Claims data are limited, while insured populations, policy wording, and control standards keep changing.

Pricing errors are most costly when rare events become portfolio-wide losses.

Research 1: online probabilistic cyber risk updating

A framework for sequentially updating cyber breach frequency and severity as new incidents or risk signals arrive.

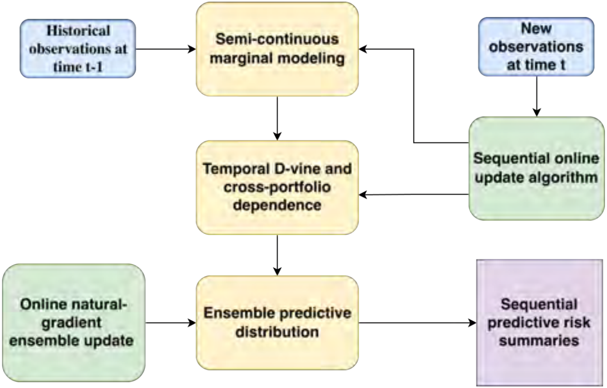
$$\widehat{F}_{i,t}(y) = \Pr(Y_{i,t+1} \leq y \mid \mathcal{D}_t, \mathbf{x}_{i,t}, \mathbf{z}_i).$$

- Cyber risk changes faster than traditional pricing and renewal cycles.
- The model produces predictive distributions, not only point estimates.
- Updated risk indications can support renewal pricing, monitoring, capital analysis, and portfolio steering.

Research outcome: sequential cyber risk modeling pipeline

What the algorithm does

- Uses historical observations to initialize marginal and dependence models.
- Incorporates new observations through sequential online updates.
- Produces predictive distributions for underwriting and portfolio monitoring.



Research 2: dependence-aware dynamic loss modeling

A deep-learning framework that captures temporal dependence, cross-group dependence, and nonlinear loss distributions for cyber risk prediction.

$$L_{\text{port},t} = \sum_{g=1}^{G} L_{g,t}, \qquad (L_{1,t}, \ldots, L_{G,t}) \text{ are modeled as dependent.}$$

How dependence is captured in the architecture:

- **Temporal attention** learns persistence and changing risk patterns over time.
- **Sector/context embeddings** allow risks to differ across industries or groups.
- **Cross-group attention** captures co-movement across related groups.
- **Mixture distribution output** represents heavy tails, zero inflation, and predictive uncertainty.

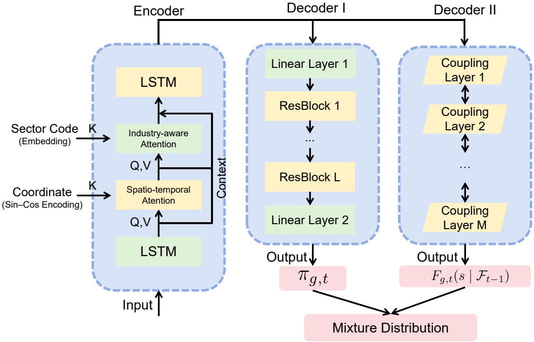
Deep learning framework: CADA-Flow

Inputs and context. Historical cyber observations are combined with sector and time information.

Encoder. LSTM and attention layers summarize temporal patterns and cross-sector context.

Decoder I. Estimates the occurrence probability, or equivalently the zero-mass component, for sparse cyber incidents.

Decoder II. Uses a context-conditioned RealNVP flow to model the conditional copula and nonlinear dependence among positive losses.



Toward next-generation cyber insurance

Future scenario: a continuous stack linking cyber telemetry, residual-risk quantification, technical pricing indications, policy support, and auditable settlement.

What changes versus today: cyber insurance moves from a static (semi-)annual quote toward a monitored, control-aware product where telemetry informs underwriting, renewal pricing, capacity, client alerts, and portfolio steering.

Near-term product design

Conclusion

- **Current pricing practice** provides the foundation: rating tables, exposure measures, policy terms, and underwriting modifiers.
- **AI can expand the information frontier** by transforming telemetry, threat intelligence, security controls, and claims signals into continuously updated risk indicators.
- **The modeling challenge** is to make these indicators actuarially useful: predictive loss distributions, tail-risk measures, dependence assessment, and explainable technical premium indications.
- **The future product** is AI-assisted underwriting, prevention, capacity steering, portfolio monitoring, and governed pricing review.

Cyber insurance is entering a new AI-enabled era: from static risk transfer to adaptive cyber risk intelligence.

Thank you!

Systemic Risk under Joint Market and Climate Stress

Presenters: Eugenia Fang and Qihe Tang

School of Risk and Actuarial Studies, UNSW Sydney

2026 International Workshop on Risk and Insurance, 29 June 2026

Outline

1. Motivation
2. Theoretical Development
   - Conditional expected shortfall
   - Multivariate regular variation
   - The main result
3. Data and Estimation
4. Empirical Findings
5. Concluding Remarks

Outline

Systemic risk

- Systemic risk refers to the risk that:
  - distress in one financial institution, sector, or market segment propagates through financial channels;
  - impairs the stability of the broader financial system;
  - potentially generates spillovers to the real economy.

- In the aftermath of the GFC, a rich body of research on systemic risk has emerged.

Systemic climate risk

- Climate change poses an additional source of systemic risk to financial stability.
  References from industry: Carney (2015), NGFS (2019), FSB (2020)
  References from academia: Dafermos et al. (2018), Monasterolo (2020), Battiston et al. (2021), Curcio et al. (2023), Pacelli et al. (2025)
- Relatively limited attention has been paid to measuring the systemic contribution of climate-related financial risks until Jung et al. (2025).
- We aim to quantify the systemic climate risk of a sector across different market and climate stress scenarios.

Market vs. climate stress

- Market stress: market-wide financial distress
- Climate stress: the manifestation of climate-related risks in financial markets
- Climate stress can trigger or exacerbate episodes of market stress, thereby constituting a distinct source of systemic risk
- Market stress may also arise from a broad range of non-climate factors.
- We examine systemic risk under a unified framework that accommodates different configurations of market and climate stress.

Compounding effect

- When climate stress and market stress materialize concurrently, it gives rise to compound climate–financial stress scenarios, with nonlinear amplification effects.
- Acharya et al. (2023) identify three mechanisms through which climate and financial crises may interact:
  - coincidental occurrence
  - shared underlying causes
  - causal propagation
- **References:** NGFS (2019), FSB (2020), Acharya et al. (2023), Engle (2023), de Bandt et al. (2025)

Physical vs. transition risk

- Within climate change risk, we focus on transition risk rather than physical risk.
- While physical risks may generate significant losses, their effects are often geographically concentrated and therefore less likely to trigger system-wide financial stress.
- By contrast, a disorderly transition to a low-carbon economy can have substantial systemic consequences through abrupt and unanticipated changes in climate policy.
- **References:** FSB (2020), Semieniuk et al. (2022), Faccini et al. (2023)

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- **References:** FSB (2020), Semieniuk et al. (2022), Faccini et al. (2023)
- **Question**: How to model transition risk?

The market-based approach

- Engle et al. (2020) build climate-news hedge portfolios.
- Jung et al. (2025) construct climate transition risk factors by forming portfolios designed to decline in value as transition policy risk rises.
- Alekseev et al. (2026) construct similar climate hedge portfolios.
- We follow this literature in adopting a market-based measure of systemic climate risk.
- **Comments:**
  - Pros: does not require internal balance-sheet data, but instead relies on market returns, hence **forward-looking and time-varying**
  - Cons: Are the proxies accurate?

Outline

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Three negative returns

- We focus on the systemic impact on a sector under joint market and climate stress.
- Three return rates, all to be specified:
  - the sector: r_i
  - the overall market: r_m
  - a transition risk portfolio: r_c
- Negative returns:

$$X_t = -r_i, \qquad Y_t = -r_m, \qquad Z_t = -r_c$$

The stress scenario

- For a distribution fucniton F, its quantile at level $0 < p < 1$ is defined by

$$F^{\leftarrow}(p) = \mathrm{VaR}_q[X] = \inf\{x \in \mathbb{R} : F(x) \geq p\}.$$

- Give a set $A \subset \mathbb{R}_+^2$, called stress set, define a stress scenario as

$$A_p = \left\{ \left(\frac{Y}{F_Y^{\leftarrow}(p)}, \frac{Z}{F_Z^{\leftarrow}(p)} \right) \in A \right\}.$$

- Typical examples for A: With suitable thresholds y_0 and z_0,
  - $(y_0, \infty) \times \mathbb{R}$: market stress
  - $\mathbb{R} \times (z_0, \infty)$: climate stress
  - $\mathbb{R}^2 \setminus \{(-\infty, y_0] \times (-\infty, z_0]\}$: either market or climate stress
  - $[y_0, \infty) \times [z_0, \infty)$: joint market–climate stress
  - $[y_0, \infty) \times (-\infty, z_0)$: market-only stress
  - $(-\infty, y_0) \times [z_0, \infty)$: climate-only stress

Conditional expected shortfall (CoES)

- Given the stress scenario A_p for (Y, Z), define the CoES as

$$\mathrm{CoES}_{p,q}\left[X|\, Y, Z\right] = E\left[X\,|X > \mathrm{VaR}_q[X], A_p\right], \qquad 0 < p, q < 1,$$

  where p controls the stress level and q controls confidence level.

- $\mathrm{CoES}_{p,q}$ measures the expected loss in the upper tail of X relative to the marginal threshold $\mathrm{VaR}_q[X]$, conditional on the stress scenario A_p.

- We have followed the spirit of Adrian and Brunnermeier (2016) but adopted a *slightly different* form for the threshold.

- **Question:** How to model X, Y, Z? **Empirical insights**: Negative returns, particularly during market downturns, exhibit heavy-tailed behavior and strong tail dependence.

Univariate regular variation

- A nonnegative random variable X, or its tail distribution function F, is said to have a regularly varying tail with index $0 < \alpha_X < \infty$, written $\overline{F} \in \mathrm{RV}_{-\alpha_X}$, if

$$\lim_{x\to\infty} \frac{\overline{F}(xy)}{\overline{F}(x)} = y^{-\alpha_X}, \qquad y > 0,$$

- Let $p = F(x) \in (0,1)$. Then we can rewrite this limit relation as

$$\lim_{p\uparrow 1} \frac{P\left(X > xy\right)}{1-p} = \lim_{p\uparrow 1} \frac{1}{1-p} P\left(\frac{X}{F_X^{\leftarrow}(p)} > y\right) = y^{-\alpha_X}.$$

- This gives hints how to extend the concept to multi-dimensions.

Multivariate regular variation (MRV)

Definition

Let $(X, Y, Z)^\intercal \in \mathbb{R}_+^3$ be a nonnegative random vector with marginal tail functions F, G, and H. The vector is said to follow a MRV structure if there exists a non-degenerate sigma-finite measure ν on $\mathbb{R}_+^3 \setminus \mathbf{0}$ such that

$$\lim_{p\uparrow 1} \frac{1}{1-p} P\left(\left(\frac{X}{F_X^{\leftarrow}(p)}, \frac{Y}{F_Y^{\leftarrow}(p)}, \frac{Z}{F_Z^{\leftarrow}(p)}\right) \in B\right) = \nu\{B\},$$

for every Borel set $B \subset \mathbb{R}_+^3$ that is bounded away from $\mathbf{0}$ and is a continuity set of ν.

Notes:

- Heavy tails: Necessarily, $\overline{F} \in \mathrm{RV}_{-\alpha_X}$, $\overline{G} \in \mathrm{RV}_{-\alpha_Y}$, and $\overline{H} \in \mathrm{RV}_{-\alpha_Z}$ for some $\alpha_X, \alpha_Y, \alpha_Z > 0$
- Tail dependence: embedded in ν

Reference: Resnick (2007)

Asymptotic estimates for the CoES

Assumption: The vector (X^+, Y^+, Z^+) jointly follows an MRV structure with indices $\alpha_X > 1$, $\alpha_Y > 0$, $\alpha_Z > 0$, and with limit ν exhibiting upper tail dependence.

Theorem

As $p \uparrow 1$ and $1 - q \sim c(1-p)$ for $c > 0$, we have

$$\lim_{p \uparrow 1} \frac{\mathrm{CoES}_{p,q}[X|\, Y, Z]}{F_X^{\leftarrow}(p)} = c^{-\frac{1}{\alpha_X}} + \frac{\int_{c^{-\frac{1}{\alpha_X}}}^{\infty} \nu\{(y, \infty) \times A\}\, dy}{\nu\left\{\left(c^{-\frac{1}{\alpha_X}}, \infty\right) \times A\right\}}.$$

Notes:

- The $\mathrm{CoES}_{p,q}$ is of the order of $F_X^{\leftarrow}(p)$.
- The right side does not involve rarity.
- Key to the right side is to estimate ν.
- Provide a theoretical foundation for estimation.

Outline

Data

Market-based framework: all risk measures are inferred from traded sector and factor returns.

- **Sample:** daily returns from 2008-01-02 to 2026-03-17.
- **Subperiods:** crisis and early post-crisis period (2008–2013), the calm pre-COVID period (2014–2019), and turbulent post-2020 period marked by COVID, inflation, political and energy shocks (2020–2026).
- **Sector ETFs:** Energy, Materials, Financials, Industrials, Technology, Consumer Staples, Utilities, Health Care, Consumer Discretionary, Transportation, and Oil and Gas.
- **Market factors:** SPDR S&P 500 ETF Trust (**SPY**) as baseline, and iShares MSCI ACWI ETF (ACWI).
- **Climate transition factors:** a low return corresponds to an increase in transition risk.
  - **EMIT:** emissions-weighted transition-risk factor; baseline
  - SA: stranded-asset factor focused on fossil-fuel-related assets
  - CEP: climate-efficient portfolio factor linked to climate news
  - SUB: brown-minus-green relative repricing factor

Sector exposure

Climate betas (126-day rolling window, controlling for SPY)

- Sectors more exposed to transition risk, such as brown sectors, are expected to have positive climate betas.
- Systemic risk rankings need not be obvious from exposure to transition climate risk alone.

Estimation workflow

Data
Negative returns
(X, Y, Z)

→

MRV diagnostic
check joint tail
dependence structure

Einmahl et al. (2025)

→

Marginal tails
Hill tail indices
$\hat{\alpha}_X, \hat{\alpha}_Y, \hat{\alpha}_Z$

Hill (1975);
Guillou and Hall (2001)

↓

Spectral measure
estimate angular
tail dependence

de Haan and Ferreira (2006);
Resnick (2007);
Wan and Davis (2019)

←

Stress set A
market, climate, joint

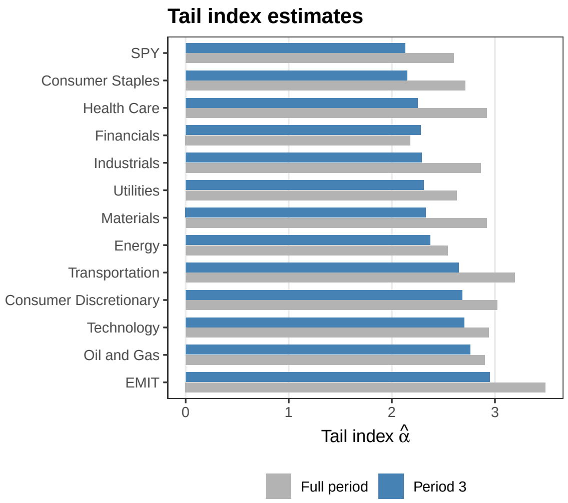
←

Plug-in CoES
compute systemic
expected shortfall

Tail inputs: Marginal tails

Marginal tails

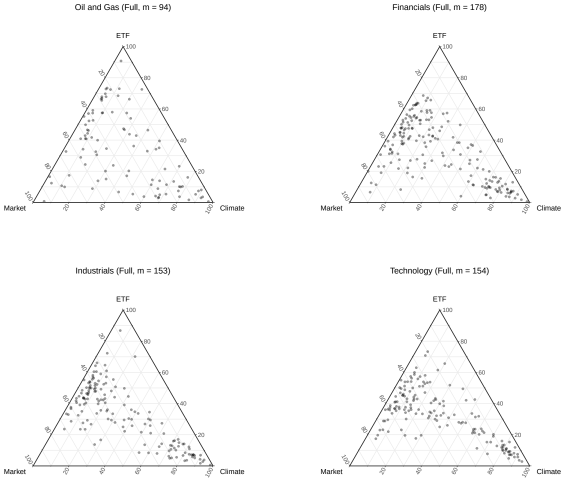
- Heavy tails of sectoral losses justify an extreme-value approach.
- Full-sample: Financials and Energy have particularly heavy sector-loss tails.
- Post-2020: Tails are often heavier across many ETFs.



Tail inputs: Tail dependence

Tail dependence

- Spectral mass is concentrated along the sector–market edge and in the simplex interior.
- Simultaneous sector–market and joint extremes.

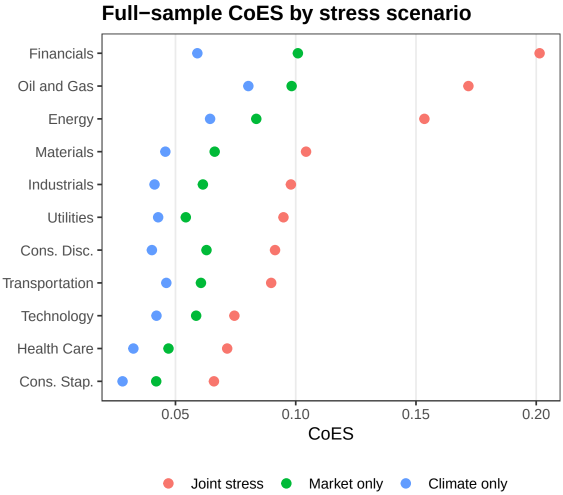


Outline

Main CoES result

CoES: Set stress level $p = 0.99$ and confidence level $q = 0.95$.

- Joint stress is more severe than standalone market or climate stress for every sector.
- Financials rank highest under joint stress.
- Oil and Gas and Energy rank highest under climate-only exposure.
- Robust under alternative combinations of market and climate factors.

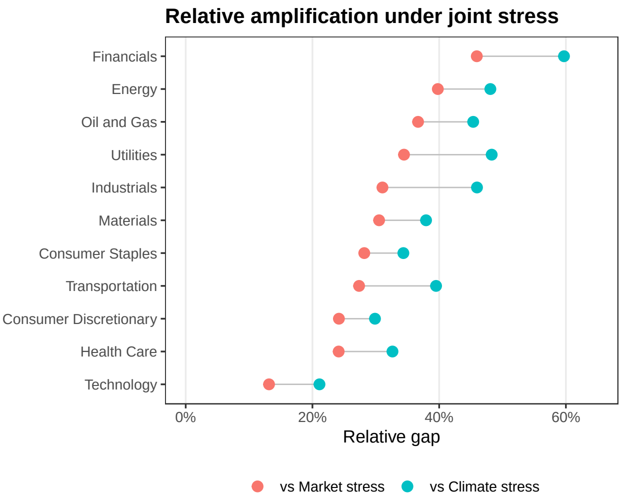


Scenario amplification: Joint vs. standalone stress

Relative gap: Full sample

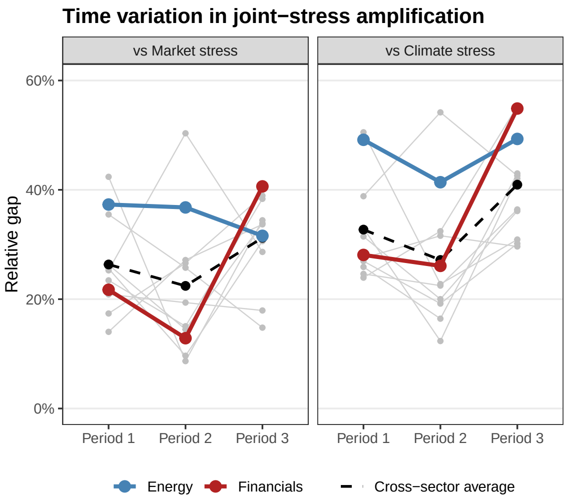
$$\frac{\mathrm{CoES}^{J} - \mathrm{CoES}^{M}}{\mathrm{CoES}^{M}}, \frac{\mathrm{CoES}^{J} - \mathrm{CoES}^{C}}{\mathrm{CoES}^{C}}.$$

- Joint-stress CoES exceeds standalone benchmarks by economically meaningful margins.
- Treating market and climate shocks separately can materially understate sector tail risk.



Relative gap: Subperiods

- Amplification is time-varying, not a fixed sector ranking.
- Period 2 shows a relative calmer environment of amplification on average, but remains sector-specific.
- Period 3, compound vulnerability becomes broader across Energy, Financials, Industrials, Materials, and Transportation.



Outline

Concluding remarks

- Theoretical contributions:
  - Focus: climate-specific sectoral systemic risk
  - Developed a market-based CoES framework
  - Conducted extreme value analysis

- Empirical findings:
  - Joint market–climate stress raises CoES for every sector and period.
  - Compound climate risk is not just a carbon-intensity ranking: Financials can be most vulnerable under joint stress.
  - Since 2020, compound vulnerability appears more broad-based across sectors.

Concluding remarks

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  - Focus: climate-specific sectoral systemic risk
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  - Conducted extreme value analysis

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  - Compound climate risk is not just a carbon-intensity ranking: Financials can be most vulnerable under joint stress.
  - Since 2020, compound vulnerability appears more broad-based across sectors.

Thank you very much!!

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Why do actuaries need to model climate risk and how they can do it?

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Conference Center, FKI Tower, Seoul, South Korea
June 29, 2026

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Project funded by Chaire DIALog, Paris

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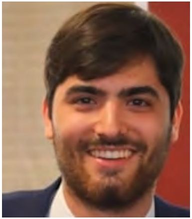

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Digital insurance and long term risk

Concordia

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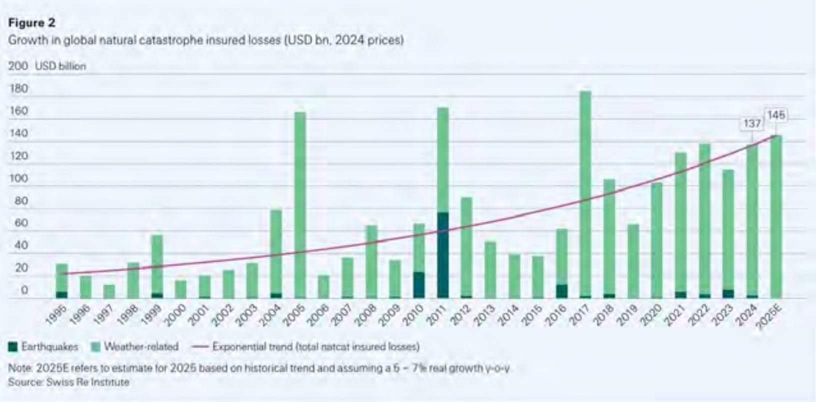
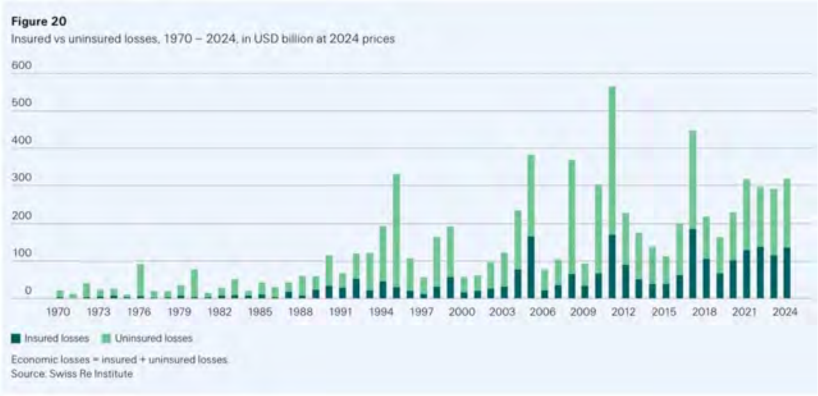
Global natural catastrophe insured losses (1995–2024)



Source : (Banerjee et al., 2025, Swiss Re)

Protection gaps for natural catastrophes (2015 – 2024)



Source : (Banerjee et al., 2025, Swiss Re)

Industry outlook

- Climate change challenges some fundamental principles of insurance : risk insurability, pooling, diversification, and risk transfer (Charpentier, 2008; Thistlethwaite and Wood, 2018; Courbage and Golnaraghi, 2022).
- Optimistic perspectives suggest that the insurance business could find in it an opportunity, through the development of new technical solutions (Rao and Li, 2023; Savitz and Gavriletea, 2019; Wagner, 2022).
- Pessimistically, climate change has forced already the strategic withdrawal of insurers in certain US markets, such as in California (Blood, 2023, APNews).

Impact on insurance costs

- In the Property & Casualty insurance sector, (Holzheu et al., 2021, SwissRe) forecasts increased frequency and severity of events due to climate change that will cost 30% to 63% more in insured catastrophe losses by 2040.
- This cost increase could even reach 90%–120% in specific markets, such as China, the UK, France and Germany.
- In all cases, it is important to add an actuarial perspective on the study of climate change and its impact on the insurance industry.

How to quantify climate risk?

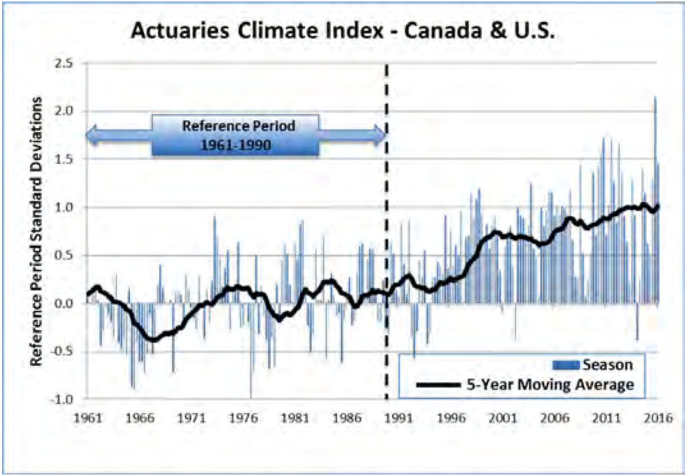
Several approaches have been proposed. For example:

- Climate indices: see the National Oceanic and Atmospheric Administration (NOAA) climate indices list.
- The Actuarial Climate Index^{TM} (ACI).
- Climate risk measures : like the climate–related expected shortfall, see (Piluso et al., 2025, IREF).

Actuarial climate indices

- The actuaries climate index™ (ACI) is linked to climate risks, a bit like the Consumer Price Index (CPI), which tracks the price variations of a basket of goods and services over time.
- Actuaries quantify and manage different types of risk. The ACI measures climate risk on the basis of a basket of extreme climate events and on variations of sea and ocean levels.
- An index increase points to an increased number of extreme climate events.

North American seasonal ACI values



Source : ACI Explore

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2. ACI historical developments

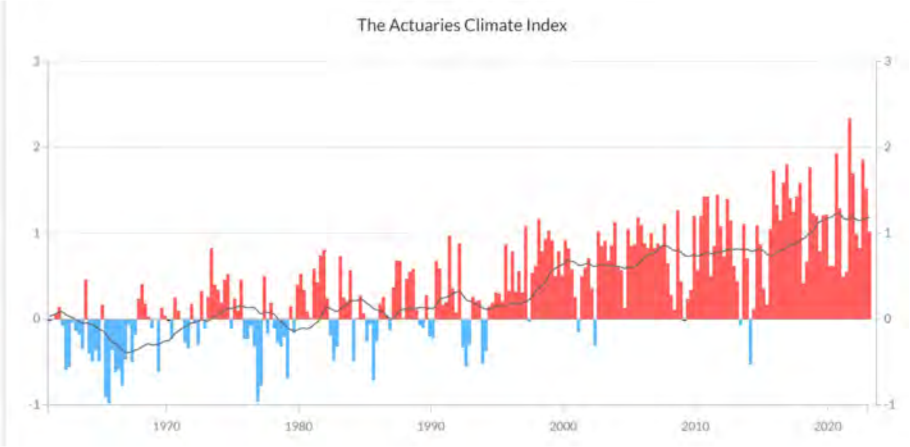
2.1 The North American ACI

Launched in April 2019, version 1.0 (current version is 1.1) [a].

- The ACI is a pedagogical tool to help inform actuaries, decision makers, and the public in general, on climate trends and their potential consequences of climate change in the US and Canada.
- An objective measure of observed climate extremes and sea levels.
- A tool to follow climate trends, updated every 3 months, separately for 12 regions, for the 2 countries, and for the North American continent.

[a] Version 2.0 is currently in development

Actuaries climate index™ (ACI)



Source : (Zhou et al., 2023, AIAE)

2.2 The UK and Australia

The UK

(Curry, 2015, IFA) considers extending the ACI to the UK and to Europe. He concludes that the definition and methodology could be applied in these regions as is, but requires appropriate data for the region.

Australia

- In November 2018, the Actuaries Institute Australia defines the AACI.
- Revised in 2025 they use a simplified version of the ACI, with 4 climate variables instead of 6, and more recent reference period : 1981–2010.

Australian Actuaries climate index (AACI)

Source : AACI component graphs and data

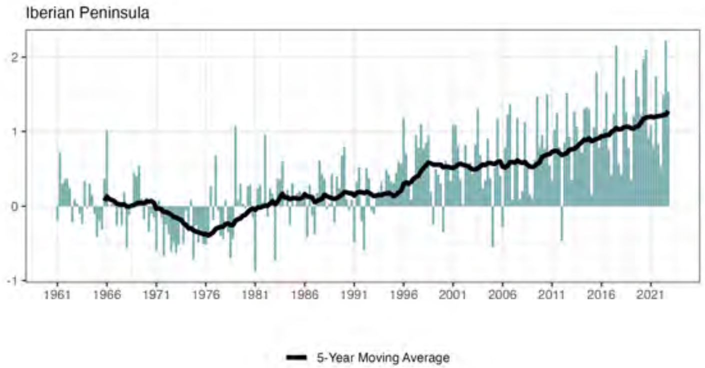
2.3 The Turkish ACI (TrACI)

- (Nevruz et al., 2022, IAD), published in the journal of the Turkish Statistical Institute, defines an ACI using the North American methodology, but for climate data only from the Ankara province.
- TrACI is defined over a different reference period (1981–2010). The paper reports TrACI values from 1981 to 2021, without including the sea level information, arguing that Ankara is not on the coastline.

2.4 The ACI for the Iberian Peninsula

- A first draft a Spanish version of the ACI was introduced in an oral presentation of the Spanish Institute of Actuaries (IAE).
- First defined over a different reference period (1975–1995 in general and 1993–2000 for sea levels).
- Their temperature variables differed also, see IAE (2023). It is now being standardized to ACI definitions, but is not yet available publicly.
- (Zhou et al., 2023, AIAE) use the North American ACI methodology and climate data for the Iberian Peninsula from the Copernicus ERA5–Land reanalysis database, see (Muñoz-Sabater et al., 2021, Copernicus), to compare the values and trends of this first European index to the North American ACI.

Iberian seasonal ACI values (IACI)



Source : (Zhou et al., 2023, AIAE)

For more details about the IACI

Anales

ON THE DEFINITION OF AN ACTUARIAL CLIMATE INDEX FOR THE IBERIAN PENINSULA

ACERCA DE LA DEFINICIÓN DE UN ÍNDICE CLIMÁTICO ACTUARIAL PARA LA PENÍNSULA IBÉRICA

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Date of reception: July 28th 2023
Date of acceptance: September 17th 2023

ABSTRACT

Climate change is defined as a long-term shift in climate patterns affecting the planet globally. The main consequences of climate change are a rise in average temperatures in many regions, and an increase in the frequency and intensity of extreme weather events, such as floods, droughts, storms, or hurricanes. Climate change is associated also with a rise in sea levels, more frequent and severe wildfires, a loss of biodiversity, and many other disruptions with serious economic impacts. These new risks are increasingly affecting both the frequency and severity of claims in different insurance branches. To help insurance companies predict and manage these new risks, actuaries have defined the Actuaries Climate Index™ (ACI), which combines information from several important weather variables from historical records of the United States and Canada. The ACI shows a significant increasing trend over the years. It is important to note, however, that the impact of climate change is not the same in all parts of the planet: different regions and countries are affected in different ways. Therefore, it is important to check if the ACI is as useful to assess climate risk outside the United States and Canada. In this paper, we follow the North American ACI methodology

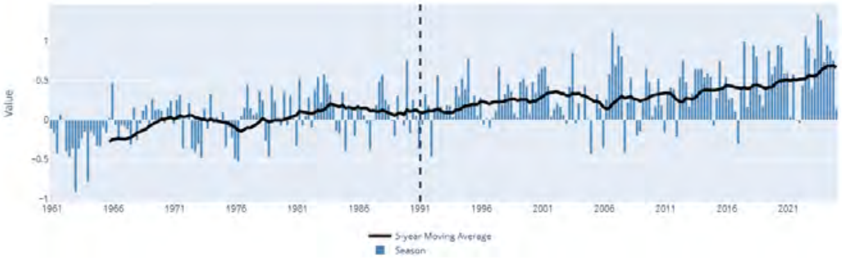
See also the R–package

And the IACI values

2.5 The French FACI

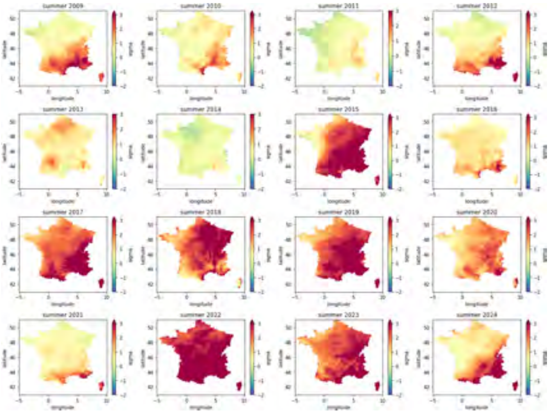
- (Garrido et al., 2023, preprint) calculate the French Actuarial Climate Index (FACI) with data extracted from the same ERA5–Land reanalysis database used for the IACI (Muñoz-Sabater et al., 2021, Copernicus).
- It is computed for over 10,000 cells forming the French grid of 0.1^o of latitude $\times$ 0.1^o of longitude (about 123.2 km^2).

French seasonal ACI values (FACI) 1961 – 2024



Source: (Garrido et al., 2023, preprint, version 2)

FACI T90 component : summers 2009 – 2024



Source: (Garrido et al., 2023, preprint, v2)

For more details: https://hal.science/hal-04684634/

See the R–package

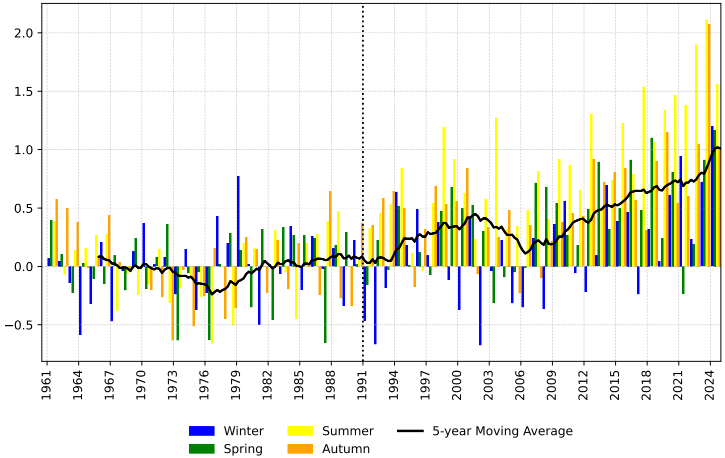
Or the Python–package

Source: (Garrido et al., 2024, Green book, CNP)

2.6 The Italian ITACI

- (Rogo et al., 2025, Risks) calculate the Italian Actuarial Climate Index (ITACI) with data extracted from the same ERA5–Land reanalysis database used for the IACI (Muñoz-Sabater et al., 2021, Copernicus).
- It is computed over the 80 km^2 cells forming the Italian grid of 0.1^o of latitude $\times$ 0.1^o of longitude.
- In this study the sea level component is assigned a different weight, depending on the number of kilometers of coastline if the region as compared to the total number for Italy.

Italian seasonal ACI values (ITACI) 1961 – 2024



Source: (Rogo et al., 2025, Risks)

2.7 The South African ACI (SAACI)

- Marais and Moutanabbir (2025), published in the journal of the South African Actuarial Journal (SAAJ), defines an ACI using the North American methodology and the same reference period of 1961–1990.
- SAACI uses ERA5 reanalysis high resolution climate data, and sea–level values from PSMSL, like the other ACI 's above.
- SAACI values are provided at the provincial and national level.

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- Apart from being a pedagogical tool, the ACI can be combined to climatic scenarios to predict future values.
- The first applications are in non–life insurance, agricultural insurance, in reinsurance or to parametric insurance (see Zhou et al., 2024, Glob.Pol.).
- Covéa has incorporated FACI to its climate risk model, thanks to the Masters thesis of Marion Favrot, who is alternating with ISFA at U. de Lyon.
- Our DIALog project focused first on the effects of climate change on human mortality and morbidity (see Garrido et al., 2024, Green book, CNP).
- New applications are being published frequently now; here is a brief overview of ACI and other indices applications.

Example 1 : ACI correlations with weather based indices for weather derivatives and crop insurance

- (Cheung et al., 2024, NAAJ) "Cointegration analysis of crop yields and extreme weather factors using actuaries climate index with application of bonus–malus system". It is a dependence analysis between crop yields and extreme meteorological factors based on the ACI. Technique: error correction model (ECM).
- (Yavrum et al., 2026, Risks) "Comparative analysis of weather–based indexes and the actuaries climate index™ for crop yield production and weather–derivative pricing". It applies the ACI to define and manage weather derivatives. The aim is to highlight the ACI's potential as a dependable benchmark for pricing weather–related financial instruments, as a competitor to the usual weather-based indexes. Techniques: functional PCA, GLMs, GAMs, XGB.

Example 2 : IACI – hailstorms for crop insurance in Spain


MDPI

Article

On the influence of climate change on hail risk in Spanish crop insurance.

Source: (Zhou et al., 2024, Risks)

Example 2 : Interpretation and other studies

Percentage increase in the 99th percentile of loss for every 0.1-unit increase in pSACI (techniques: mixed linear and quantile regression models):

- In the province of La Rioja, 21,96%.
- In the province of Cuenca, 20,79%.
- In the province of Albacete, 19,62%.
- In the province of Ciudad Real, 19,61%.
- In the province of Toledo, 17,80%.

Consistent with prior research in the wine economics literature, on the impact of weather events on insurance in the viticulture sector in Spain. See (Martínez-Salgueiro, 2019, WEP), who uses weather-based indices, as a meteorological risk management alternative in viticulture.

Example 3 : Parametric insurance based on FACI

The rating formula for a basic parametric insurance is defined by 3 variables: the entry point E, the exit point X and the marginal value of 1 extra index unit, say IU.

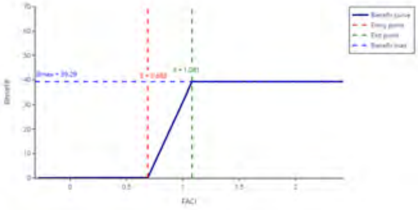
The insurance benefit payments are determined by :

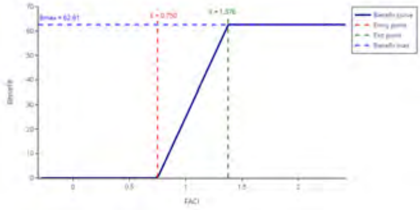
$$B = IU \ x \ \mathbb{1}_{[I>E]} \ x \ \min\{I - E, X - E\},$$

where B is the benefit value, $\mathbb{1}_{[A]}$ is an indicator function of event A and I is the index value.

This linear benefit formula is the most common on the market.

Example 3 : Parametric insurance benefit examples

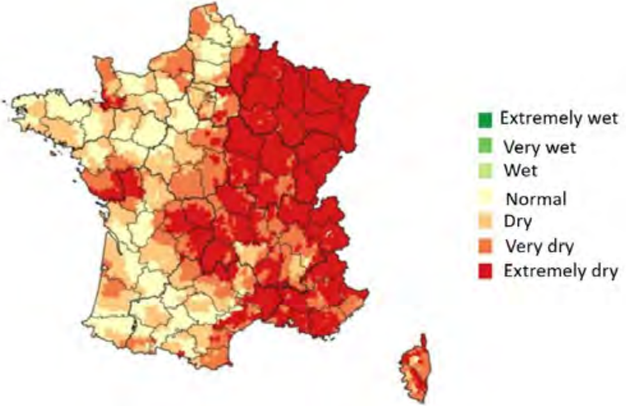




E = median , E = mean ,
X = 75%-percentile X = 90%-percentile

Source: (Garrido et al., 2023, preprint)

Example 4 : Standardized Soil Wetness Index, Météo–France, 2018



Source: (Heranval et al., 2023, EAJ)

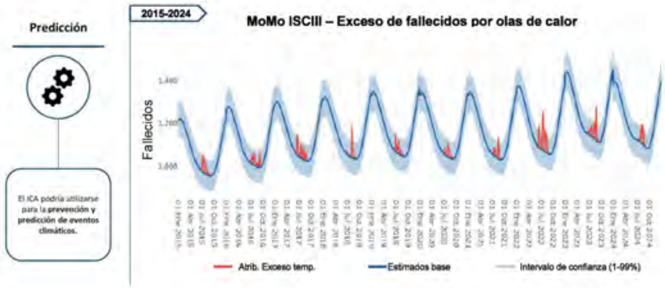
Example 5 : Impact of heat waves on excess mortality

What is excess mortality?.

- The actuarial approach consists in removing the seasonality and the improvement trend from the oberved mortality. What is left is considered excess mortality. On this basis it can be compared to climate extremes, socio—economic and/or environmental variables.
- Another approach consists in using mortality data by cause of death, to identify those due to heat wages.

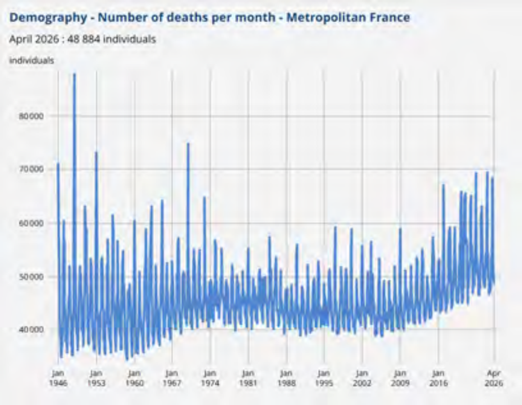
Example 5 : Impact of heat waves on mortality in Spain

Using climate date from the Spanish meteorological agency (AEMET), the Spanish Institute of Actuaries (IAE) studied also the impact of extreme high temperatures on excess mortality.



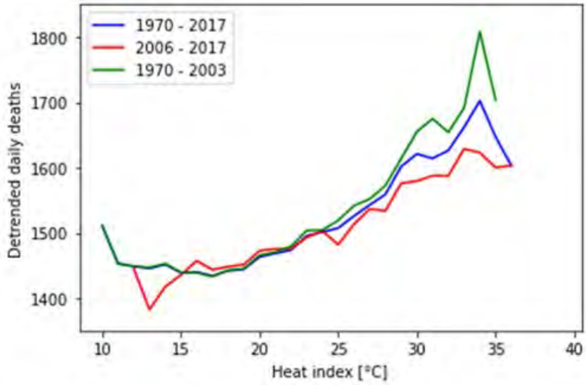
Source: IAE -– working group on climate risk

Example 6 : Mortality per month in France, 1946 – 2026



Source: INSEE – Number of deaths per month – Metropolitan France

Example 6 : Impact of heat waves in France, 1970 – 2017



Source: (Garrido et al., 2024, Green book, CNP)

Survey of current research, climate vs mortality – I

Current research on the impact of climate extremes on life and health insurance :

- (Milhaud and Gouthon, 2024, preprint) "Impact of above–average heat on mortality: extension of longevity models to account for global warming". Techniques: Seklecka's extension of Lee–Carter model.
- (Madaniyazi et al., 2024, Lancet) forecast the seasonality of mortality under climate change.
- (Shen et al., 2024, SR) Mortality rate prediction in European population clusters. Techniques: deep learning and multiscale analysis.
- (Raynal and Loisel, 2025a, AAS) "Mortality modeling for short term climate stress test in France : impact of extreme heat". Techniques: clustering, Poisson regression.

Survey of current research, climate vs mortality – II

- (Loisel et al., 2025, preprint) “Recommendations and challenges regarding the construction of climate change impact scenarios in health and life insurance”.
- (Bégin et al., 2025, IME) model seasonal mortality, including climate effects. Technique: age–period–cohort approach.
- (Morreeuw, 2025, thesis) actuarial Master’s thesis “Prédiction de la mortalité estivale française par l’UTCI”, supervised by Anani Olympio (CNP, Paris). Techniques: regression, random forest.
- (Guibert et al., 2025, IJF) “Impact of climate change on mortality: An extrapolation of temperature effects based on time series data in France”. Technique: DLNM.

Survey of current research, climate vs mortality – III

- (Barigou et al., 2025, preprint) "Mortality Modeling and Forecasting with the Actuaries Climate Index". Techniques: GLMs, GAMs, XGB.
- (Robben et al., 2026a, JRSS) studies the short–term association between environmental factors, like weather and air pollution, and weekly mortality rates in small European regions.
- (Robben et al., 2026b, IME) "Granular mortality modeling with temperature and epidemic shocks: a three–state regime–switching approach".
- (Zheng et al., 2026, AAS) "A brief review of deep learning methods in mortality forecasting".

Survey of current research, climate vs mortality – IV

Also on other topics:

- (Raynal and Loisel, 2025b, preprint) "Risk averse asset allocation in a context of climate change with reinforcement learning and hidden Markov models".
- (Albrecher and Loisel, 2026, EAJ) "The insurance of climate–related physical risks: challenges and opportunities for actuaries".

Conclusions – I

- Hopefully, the recent indices calculated for Spain, Portugal, France and Italy constitute one more step towards the definition of a European index.
- New ACIs are currently in the design stage, for instance for Marocco (A. Bouchaikh, G. Ghazzali and A. Oulidi, Atlantic Re, Casablanca), for Turkiye (Cem Yavrum, A. Sevtap Selcuk-Kestel, Middle East Technical U., Ankara), for Saudi Arabia and for the UK.
- Covéa, the lasgest P&C insurer in France, has incorporated FACI to its climate risk model, thanks to the Masters thesis of Marion Favrot, who is alternating with ISFA at U. de Lyon.
- We are revisiting the choice of variables included in these ACI's, the choice of reference period and the quantiles chosen (90/10%); using time penalized trees (TPTs) to rank variable importance.

Conclusions – II

- The use of standardized anomalies (Z–scores) is also under review. With Alejandro Balbás, Silvia Mayoral and Rosa Rodriguez (U. Carlos III, Madrid) we use a risk measure approach to climate risk.
- The North American ACI joint Task Force is working on a redesign (version 2.0); see the CAS presentation and the video recording Data Disclosure for the Actuaries Climate Index™.

Thank you for your attention!

Any questions?

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Weather-Informed Insurance Ratemaking and Product Management

Peng Shi[a]

Joint work with Zhengxiao Li[b] and Yifan Huang[b]

[a] University of Wisconsin-Madison
[b] University of International Business and Economics

Agenda

1. Classic experience rating
2. Incorporating weather information via a varying-coefficient model
   - Deep learning to encode weather information
   - Multi-task learning approach to allow forward-looking prediction
3. A case study in automobile insurance
4. Summary and concluding remarks

Classic Pricing and Experience Rating

Initial pricing:

- create homogenous risk classes based on rating variables
- premium is based on expected losses

Experience rating:

- adjust renewal premium based on claim history
- examples are credibility and bonus-malus

Classic Pricing and Experience Rating

- Weather-related hazards pose significant financial risks to individuals and businesses
- In automobile insurance, weather may affect claim likelihood through different channels
  - Adverse weather conditions can directly increase accident risk
  - weather may indirectly alter risk by influencing policyholder behavior
- In practice, however, weather information is rarely incorporated explicitly into insurance ratemaking

Project Overview

- We aim to develop a weather-informed framework for insurance ratemaking and product management
- We propose a deep varying-coefficient framework for longitudinal insurance claim counts that supports both initial underwriting and renewal pricing.
  - We use encoder–decoder architecture that maps multi-year historical weather sequences into weather-responsive pricing coefficients.
  - we introduce an auxiliary learning task that encourages the model to extract forward-looking weather patterns.

Basic Setting

- Consider a portfolio of n policyholders observed over T periods.
  - T_i denote the number of observed policy years for policyholder i, so that $T = \max\{T_1, \ldots, T_n\}$
  - y_{it} denote the number of claims by policyholder i in coverage period j,
  - $\boldsymbol{x}_{ij} = (x_{ij,1}, \ldots, x_{ij,q_x})'$ be a q_x–dimensional vector of rating variables

- We consider the classical Poisson–Gamma model for longitudinal count data

$$Y_{ij} \mid \Theta_i \sim \text{Poisson}(\lambda_{ij}\Theta_i), \text{ with } \Theta_i \sim \text{Gamma}(\alpha, \alpha)$$
$$\log \lambda_{ij} = f(\boldsymbol{x}_{ij}; \boldsymbol{\beta}) = \boldsymbol{x}'_{ij}\boldsymbol{\beta}$$

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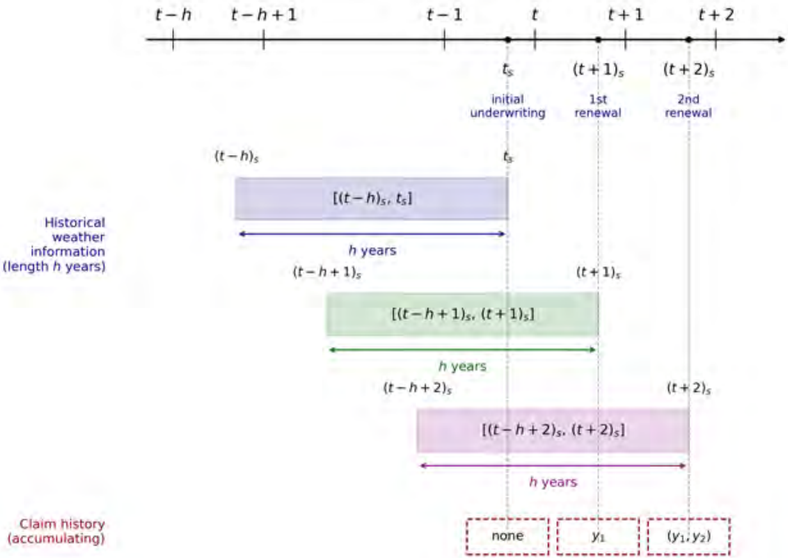
Weather Information



Varying Coefficient Model

We consider a varying-coefficient extension:

$$\log \lambda_{ij}(\boldsymbol{z}_{i[(t+j-1)_s,h]}, \boldsymbol{x}_{it}) = \log d_{ij} + \beta_0(\boldsymbol{z}_{i[(t+j-1)_s+,h]}) + \sum_{l=1}^{q_x} \beta_l(\boldsymbol{z}_{i[(t+j-1)_s,h]}) x_{it,l},$$

- Weather information is policyholder specific
- Regression coefficients remain interpretable

Multi-task Learning

A temporal mismatch: the risk-relevant weather and the historical information at pricing

We introduce a multi-task learning framework that jointly models

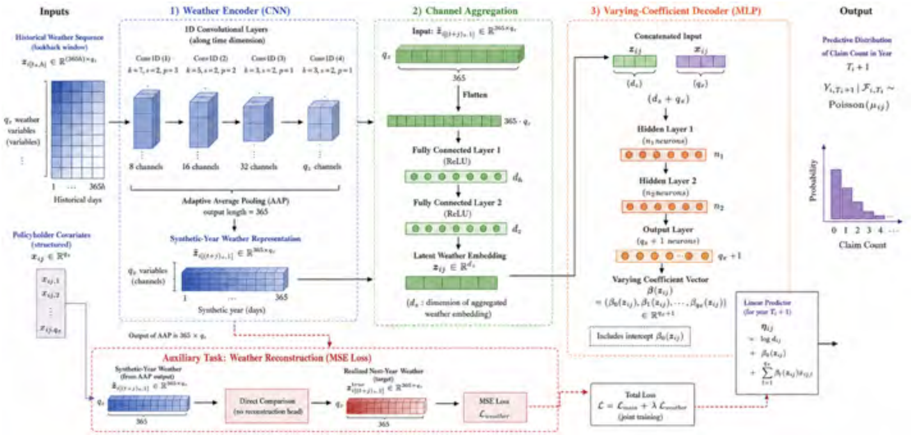
- claim frequency
- a forward-looking representation of policy-year weather

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{claim}} + \gamma \cdot \mathcal{L}_{\text{weather}}$$

where

$$\mathcal{L}_{\text{weather}} = \frac{1}{T_i} \sum_{j=1}^{T_i} \frac{1}{365\, q_z} \left\| \tilde{\boldsymbol{z}}_{i[(t+j)_s,1]} - \boldsymbol{z}^{\text{true}}_{i[(t+j)_s,1]} \right\|_F^2 .$$

Multi-task Learning Architecture



Data

Data are collected via two sources:

- A longitudinal automobile insurance dataset covering a portfolio of policyholders, including their claim outcomes and associated rating variables
- A multidimensional time series of daily weather measurements recorded at meteorological stations

Data: Insurance

Table: Empirical distribution of claim counts by year and overall.

Count	Percentage by Year					
	2010	2011	2012	2013	2014	Overall
0	73.76%	75.71%	76.30%	77.53%	82.28%	77.62%
1	16.86%	16.04%	15.75%	15.38%	13.82%	15.38%
2	6.24%	5.74%	5.79%	5.53%	3.19%	5.18%
3	2.13%	1.84%	1.63%	1.29%	0.58%	1.38%
4+	1.01%	0.66%	0.53%	0.27%	0.13%	0.44%
obs.	14,065	23,598	31,315	41,581	30,942	141,501

Data: Insurance

Table: Description and summary statistics of rating variables.

Variables	Type	Description	Mean	SD
exposure	numeric	policy exposure (in years)	0.98	0.07
age	numeric	driver's age (in years)	39.40	9.08
carage	numeric	age of the vehicle (in years)	4.01	2.94
carvalue	numeric	vehicle purchase price (in RMB)	97,228	88,558
gender	categorical	driver's gender		
		male	68.32%	
		female	24.95%	
		unknown	6.73%	
cartype	categorical	vehicle type		
		sedans	70.82%%	
		wagons	19.99%	
		SUVs	7.02%	
		microcars	2.17%	
carorigin	categorical	origin of the vehicle		
		joint-venture	53.98%	
		domestic	43.73%	
		imported	2.29%	

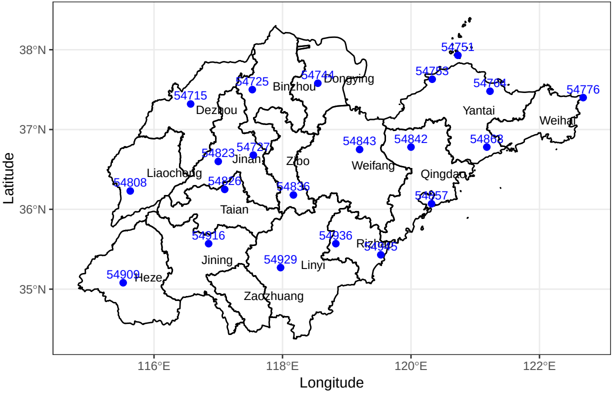
Data: Insurance

Table: Description and summary statistics of rating variables.

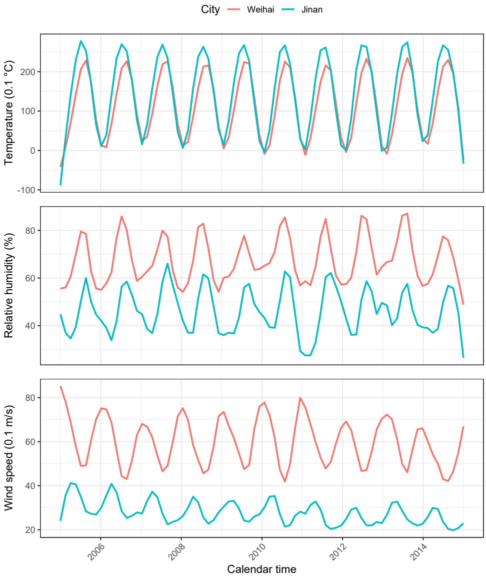
Variables	Type	Description	Mean	SD
`svolume`	categorical	engine displacement (swept volume)		
		$\leq$1.0L	16.48%	
		1.1–1.6L	55.54%	
		1.7–2.4L	23.93%	
		$\geq$2.5L	4.05%	
`carseats`	categorical	number of seats in vehicle		
		< 6 `seats`	82.41%	
		≥ 6 `seats`	17.59%	
`coverage`	categorical	type of coverage		
		`mandatory only`	34.05%	
		`mandatory and voluntory`	65.95%	

Data: Weather

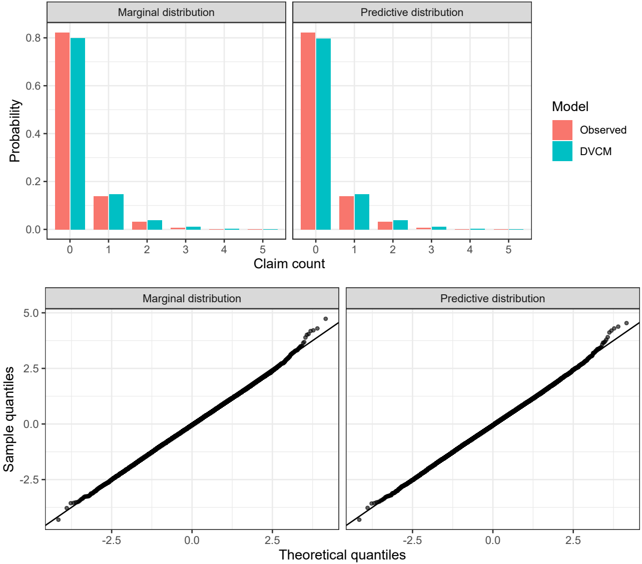
We use daily measurements of eight meteorological variables from stations in Shandong Province, corresponding to the region covered by the insurance data.



Data: Weather



Out-of-sample Calibration



Prediction Comparison

We consider the following two modeling frameworks:

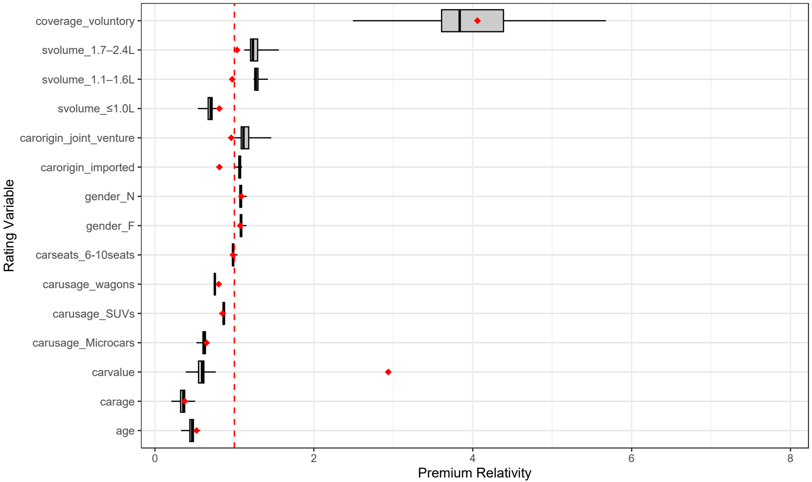
- Baseline model: A classical Poisson regression model for longitudinal count data with gamma-distributed random effects.
- Deep varying-coefficient model (DVCM): The proposed varying-coefficient Poisson regression model.

Table: Ordered Gini indices for champion–challenger comparisons†.

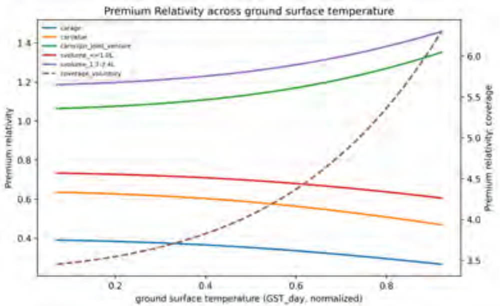
Base Premium	Marginal Distribution	Predictive Distribution
Baseline model	22.88 (0.80)	20.15 (0.96)
DVCM	-30.88 (0.77)	-21.76 (0.96)

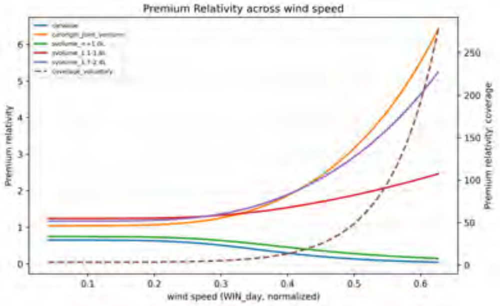
† Standard errors are reported in parentheses.

Implications: Relativity

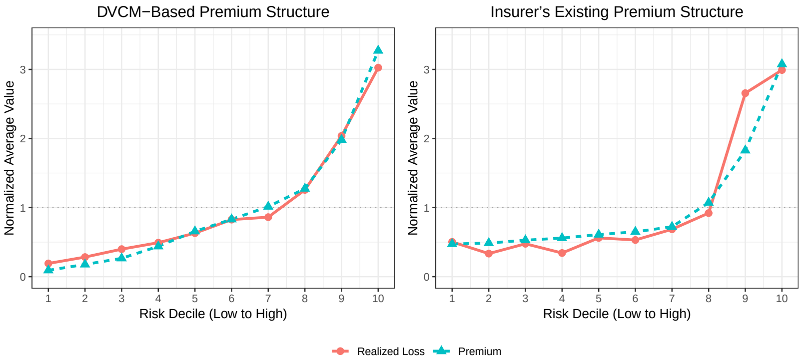


Implications: Relativity





Comparison with Current Premium



Conclusion

- Developed a deep varying-coefficient framework that incorporates weather information into automobile insurance pricing while preserving actuarial interpretability.
- Weather information improved risk differentiation and generated substantial heterogeneity in premium relativities and Bonus–Malus adjustments.
- Results suggest weather affects insurance risk through both baseline claim frequency and interactions with traditional rating factors.
- Future insurance pricing systems may become increasingly adaptive to changing environmental conditions.

Assessing Driving Risk using Telematics Data a Wavelet Transform Approach

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Collaborators: Andrei Badescu, Jongtaek Lee

June 29, 2026

Outline

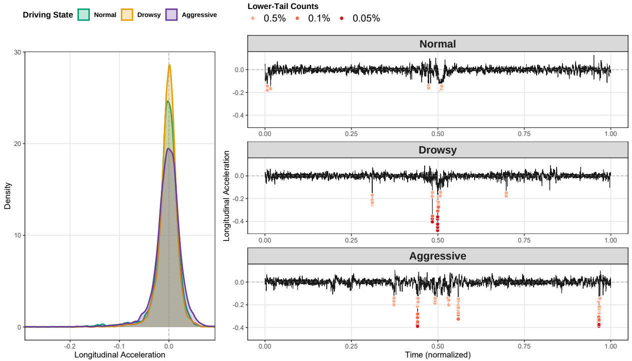
Background and Motivation

- This project was stemmed from multi-year collaboration between our group and Geotab Inc, a global leader in connected transportation solutions and telematics data collection and management.
- We have been involved in some of their projects on real-world telematics problems.
  - *Assessing driving risk with enriched telematics signals*
  - *Collision detection using high-rate telematics data*
  - *Identifying hazardous driving areas and accident propensity*
  - *Telematics-driven vehicle-driver predictive safety benchmarking for fleet operations*
  - *Weight detection for heavy-duty vehicles*
- All of these projects are centered at evaluation and classification of driving risk at both the trip level and the driver level, and in a data-driven way.

From Insurance Perspective

- From an actuarial viewpoint, the core objective is not only prediction, but also **risk differentiation, ranking and quantification - pricing**.
- Although telematics data, as time series data, provide very rich behavioral information of drivers at the trip level, most research use drivers' attributes (as covariates) and summary statistics of trips, and employs a regression modelling framework.
- Such an approach clearly has issues:
  - it does not fully utilize the rich behaviour information embedded in telematics data.
  - Summary statistics are sensitive to how they are calculated and often problematic, especially when the trip length and the scale of event count varies from trip to trip and from driver to driver.
  - a small change can have a significant effect on a regression model.
  - As a result, accurate quantifying and ranking the risk of trips and drivers across the board can be challenging.

How Do Driving Behaviours Look like?



- In order to quantify driving risk one must take two factors into account: how often risky behaviour occurs and how severe it is.

Our Approach

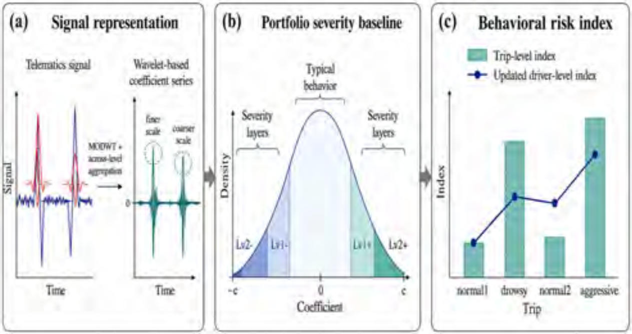


Figure: Panel (a): how telematics signals of each trip are transformed into a wavelet-based representation. Panel (b): the fitted severity model where the Gaussian component describes typical patterns, while Uniform layers represent increasingly extreme patterns. Panel (c): an example of trip-level index for each behavioral state and sequentially updated driver-level index.

MODWT for Telematics Data

- Telematics signals are time series data with rich local temporal structure.
- Risk-relevant behaviours such as:
  - harsh braking,
  - harsh/sudden acceleration,
  - short bursts of oscillation,
  - sustained abnormal manoeuvres

  are often localized in time and may occur at different durations.
- Wavelets are attractive because they naturally capture:
  - short-lived local deviations at fine scales.
  - longer sustained patterns at coarser scales.
- This makes wavelet representations especially suitable for extracting risk-relevant transient driving patterns.

Data Representation

- For trip j, let the longitudinal acceleration signals be

$$X_j = (X_{j,t})_{t=0}^{T_j-1}.$$

- For level l, MODWT produces wavelet coefficients

$$\widetilde{W}_{j,l,t} = \sum_{k=0}^{K_l-1} \widetilde{h}_{l,k} X_{j,(t-k) \bmod T_j}, \qquad t = 0, \ldots, T_j - 1,$$

  where filters $\widetilde{h}_{l,k}$ at level l are generated from the *Daubechies D4* wavelet filter through dyadic dilation.

- Interpretation:
  - small $l \Rightarrow$ short-duration local changes,
  - large $l \Rightarrow$ smoother, longer-duration changes.
  - in general, 6 levels is sufficient to capture driving behaviour changes.

Across-Level Aggregation

- A risky manoeuvre need not appear at only one level (or scale).
- Hence, we aggregate the MODWT coefficients across selected levels:

$$C_{j,t} = \max_{l \in \mathcal{L}} \left| \widetilde{W}_{j,l,t} \right|, \qquad t = 0, \cdots, T_j - 1,$$

  where $\mathcal{L} = \{1, \ldots, L\}$.
- Interpretation:
  - at each time point, $C_{j,t}$ records the largest multi-scale deviation,
  - so short, medium, and long abnormal patterns all compete to be represented.
- This yields a single trip-level time series

$$C_j = (C_{j,0}, \cdots, C_{j,T_j-1}).$$

Modelling Severity of Acceleration/Braking

- All the trip level time series data are sampled by a hierarchical sampling with thinning within each of the trips.
- The retained time series data are then pooled to form a sample that serves as an input to the portfolio-level severity model.
- The central idea:
  - typical behaviour should define a stable baseline,
  - abnormal behaviour should be absorbed by explicit tail components.
- A Gaussian–Uniform mixture is used and fitted with a specific EM algorithm:
  - Gaussian component(s): normal/typical driving behaviour,
  - multiple Uniform components on the left and right tails:
    - left tail = harsh braking/deceleration;
    - right tail = harsh acceleration.
- Each Uniform component defines a severity layer.
- Layers farther from the center correspond to:
  - rarer behaviour,
  - more extreme behaviour.

Why to Use the Gaussian–Uniform Mixture Model?

- Longitudinal acceleration often has an approximately Gaussian central behaviour.
- But a pure Gaussian fit is problematic for telematics risk scoring:
  - tail extremes inflate the fitted variance,
  - the "normal" baseline becomes unstable,
  - abnormality becomes sensitive to portfolio composition in terms of drivers' style.
- By explicitly allocating tail observations to Uniform components:
  - the Gaussian core remains stable and interpretable,
  - the tail is structured into ordered rarity layers,
  - severity is measured at a common portfolio-level scale.
  - such an approach allows for meaningful comparison across trips and across drivers, even when trip lengths and driving styles differ.

Modeling Signal Count within Each Layer

- Once the severity layers are estimated, each $C_{j,t}$ is assigned to: a left-tail layer, a right-tail layer, or the Gaussian core.
- For trip j, we count how often the signal enters each layer:

  Multi-Layer Tail Counts (MLTC)

- Thus, a trip is summarized not only by: how many abnormal patterns occur, but also by how deep into the tails.
- Layer-wise counts are modeled using a Poisson–Gamma model.
- The resulting posterior weighted intensity with weights proportional to severity, yields:
  - an exposure-normalized trip-level (behaviour) risk index, and
  - allows sequential Bayesian updating at the driver level.

A Controlled Study: Data Description

- We apply the proposed framework to a labelled dataset 'UAH-DriveSet' from

  Romera, E., Bergasa, L. M. and Arroyo, R. (2016) "Need data for driver behaviour analysis? presenting the public UAH-driveset." In *2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)*, pp. 387–392. IEEE.

  to validate its effectiveness in anomaly detection.

- *Five* different drivers and vehicles are asked to perform three distinct driving behaviour (normal, aggressive and drowsy) on two different roads (a motorway and a secondary road).

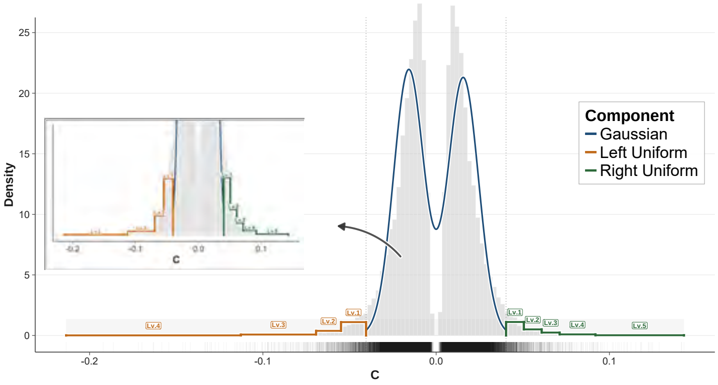
- Telematics recording starts when the vehicle enters the specific road and ends when it exits, hence speed is always non-zero.

- Note that none of the drivers has been involved in accidents, which is not as useful from an actuarial perspective.

- We are currently working closely with Geotab to acquire their collision data for this project.

Fitting Severity Model

- We fit the severity and frequency components using all 40 trips pooled across secondary and motorway roads.
- This creates a common portfolio baseline and common severity scale.



Frequency–Severity Representation for Trip j

For trip j, let

$$C_j = (C_{j,0}, \cdots, C_{j,T_j-1})$$

be the aggregated MODWT coefficient series.

Using the fitted portfolio-level Gaussian–Uniform mixture model, each coefficient is assigned into one of the ordered severity layers:

$$\Theta_1, \Theta_2, \ldots, \Theta_M,$$

where deeper tail layers correspond to more extreme driving behaviour.

For layer m, define the layer-wise count

$$N_{j,m} = \sum_{t=0}^{T_j-1} \mathbf{1}(C_{j,t} \in \Theta_m),$$

which represents how often trip j exhibits severity level m behaviour.

Behaviour Risk Index

For each severity layer m, we model

$$N_{j,m} \mid \lambda_{j,m} \sim \text{Poisson}(E_j \lambda_{j,m}),$$

where:

- E_j = exposure (trip length),
- $\lambda_{j,m}$ = latent risk intensity for layer m.

Using the conjugate prior

$$\lambda_{j,m} \sim \text{Gamma}(\alpha_m, \beta_m),$$

the posterior mean becomes

$$\widehat{\lambda}_{j,m} = \frac{\alpha_m + N_{j,m}}{\beta_m + E_j}.$$

The proposed frequency–severity trip-level risk index is

$$R_j = \sum_{m=1}^{M} w_m \, \widehat{\lambda}_{j,m},$$

where:

- w_m are severity weights,
- larger weights are assigned to deeper tail layers.

Behaviour Risk Index

Driver	Label	Exposure (E_i)	Behavioral Risk Index ($\times 10^{-4}$) Trip	Driver
D1	normal1	411	3.47	3.47
	aggressive	354	**15.64**	9.49
	normal2	435	5.42	7.75
	drowsy	335	**14.89**	9.75
D2	normal1	434	4.32	4.32
	aggressive	411	**34.84**	20.83
	normal2	458	4.31	15.01
	drowsy	434	**20.52**	17.52
D3	normal1	466	3.09	3.09
	aggressive	452	**10.44**	6.21
	normal2	446	4.28	4.99
	drowsy	442	**7.98**	5.51
D4	normal1	486	3.14	3.14
	aggressive	441	**11.09**	6.46
	normal2	460	3.69	4.92
	drowsy	458	**6.41**	4.95
D5	normal1	467	3.97	3.97
	aggressive	282	**41.59**	19.93
	normal2	462	6.27	14.72
	drowsy	467	**6.43**	12.27
D6	normal	519	6.75	6.75
	drowsy	480	**11.20**	8.99

Behaviour Risk Index

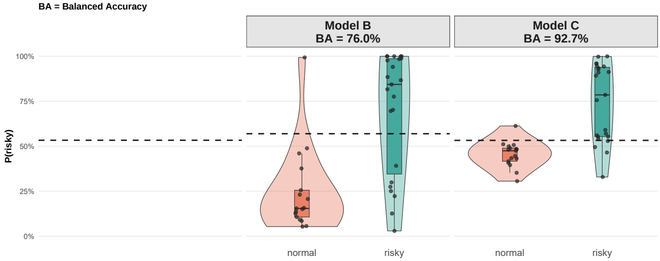
- The proposed index provides a coherent cross-trip ranking because all trips are measured against the same portfolio-level severity scale.
- In the controlled study:
  - risky trips (aggressive/drowsy) generally have higher trip-level risk than normal trips,
  - but the reason can differ:
    - aggressive: often more frequent abnormal patterns across many layers,
    - drowsy: sometimes low frequency with deeper tail penetration.
- Interpretation:
  - normal trips tend to have smaller MLTC totals and shallower layers,
  - aggressive trips tend to spread mass across multiple layers,
  - drowsy trips can have fewer total counts but reach deeper layers.

Binary Classification Validation

- We validate the proposed framework by a binary task:

  normal vs. risky (aggressive or drowsy)

- Two models are compared:
  1. Model B: layer-wise counts only,
  2. Model C: proposed joint frequency–severity risk index.



Contributions of this Approach

- This approach is fully signal-driven:
  - no claims labels,
  - no demographic or vehicle covariates,
  - no manually defined harsh-event thresholds.
- It contributes three things simultaneously:
  1. a time-series representation that preserves local driving dynamics,
  2. a formal notion of severity anchored to portfolio-level rarity,
  3. a dynamic trip-to-driver updating mechanism.
- From an actuarial viewpoint, this is attractive because it supports:
  - trip-level ordering,
  - driver-level monitoring,
  - dynamic UBI-style pricing,
  - reduced dependence on potentially biased traditional covariates.

Ongoing Project

- Currently we use only longitudinal acceleration.
- The next extension is multivariate:
  - longitudinal acceleration,
  - lateral acceleration,
  - speed as a contextual modifier.
- Why multivariate?
  - driving manoeuvres such as drifting, harsh cornering, lane-changing, or tailgating are better characterized jointly.
- Proposed direction:
  - perform level-wise motif discovery on multivariate wavelet-based signals,
  - identify candidate local patterns,
  - consolidate nearby patterns in time/scale into one event instance,
  - define risk at the event level rather than the pattern level.

Thank you for listening!

This presentation is based on the following working paper:

Lee, J., Badescu, A.L. and Lin, X.S. (2026). "A portfolio-anchored frequency–severity behavioral risk index for trip and driver assessment using telematics signals".

actsci.utstat.utoronto.ca

清華大學
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Tokenization of DeFi Insurance

Runhuan Feng

School of Economics and Management
Tsinghua University

June 29, 2026

2026 International Workshop on Risk and Insurance

清華大學
Tsinghua University

Outline

Why Innovations?

Challenges with Current Insurance Market:

- Prohitive capital requirements
- Stringent regulatory oversignt
- The "brand and reputation" barrier
- High customer acquisition costs

Discruptive Innovations:

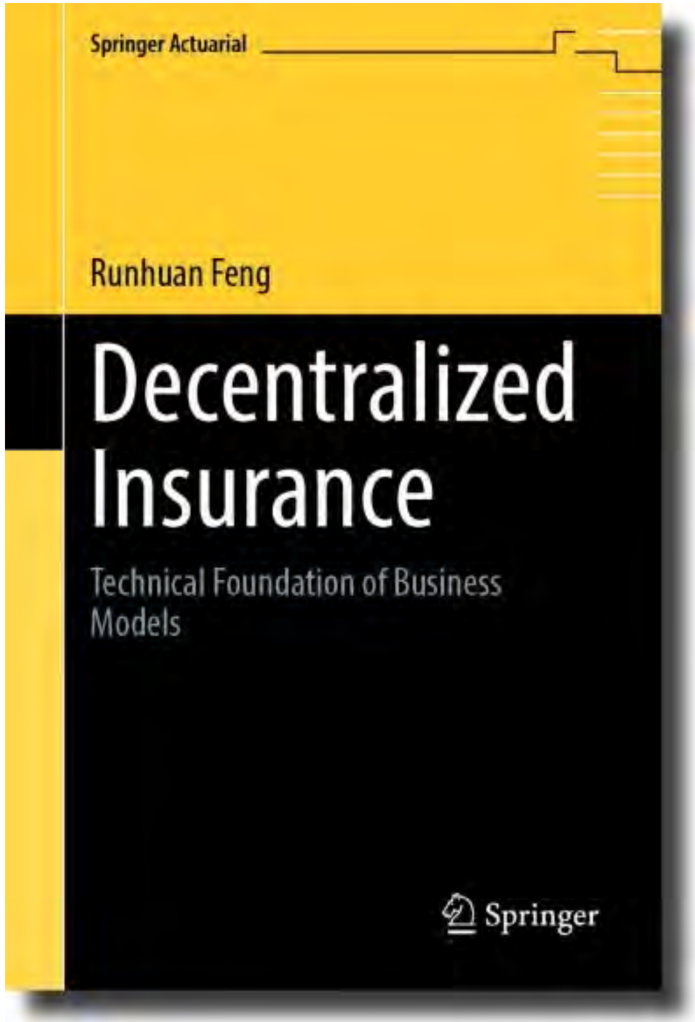
- Low-end disruption
- New-market disruption

Market Innovations

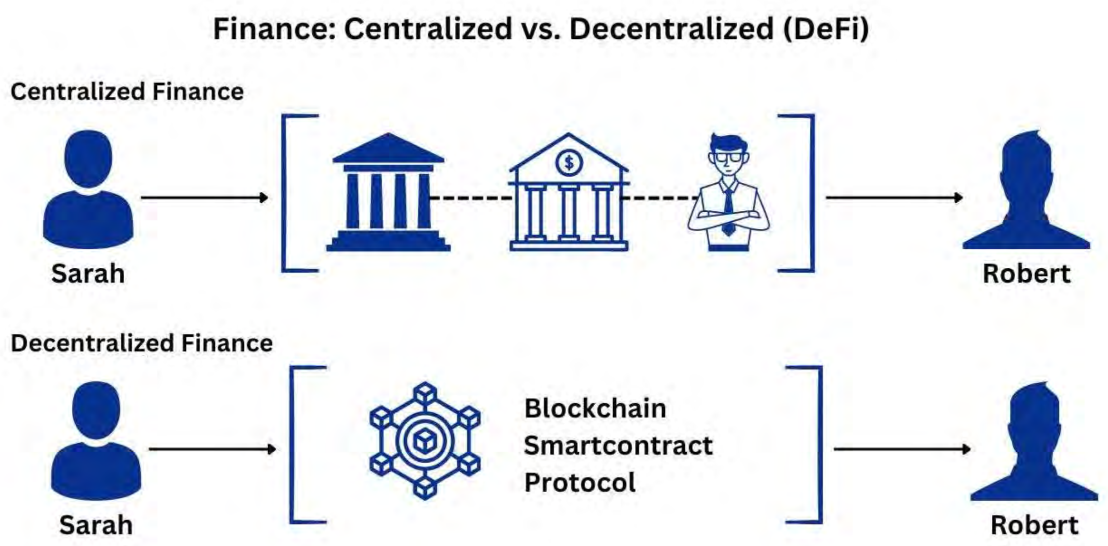
- Decentralized insurance
- Distributed risk sharing
  - DeFi insurance (You are here)
  - Distributed insurance

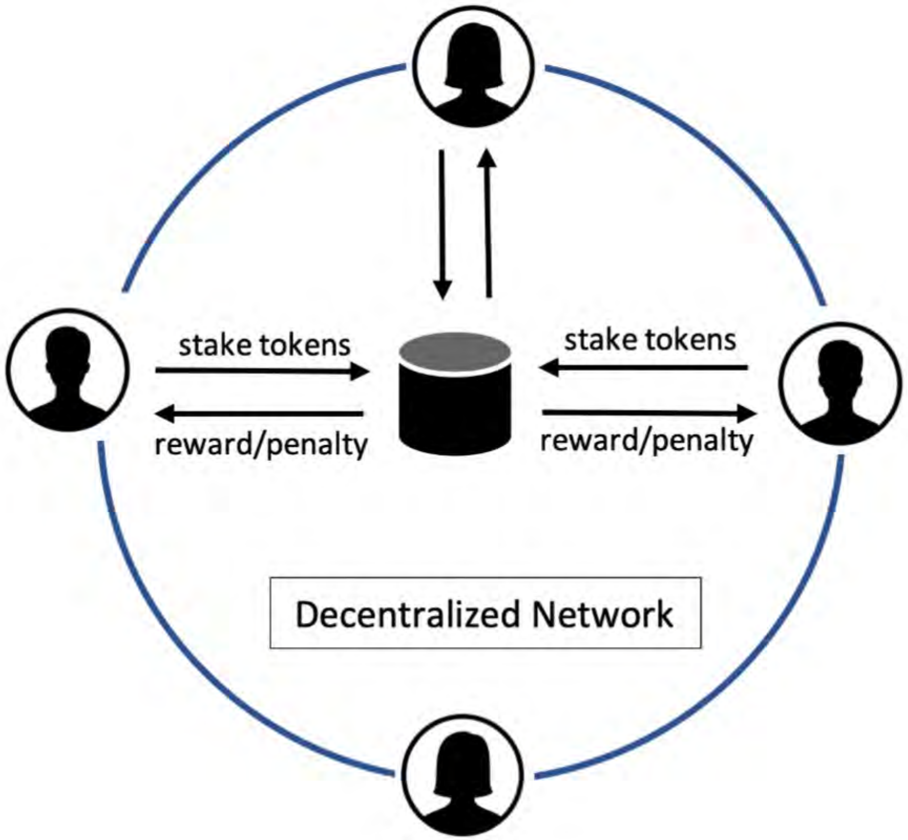
  (Day 1 Tue. 15:40 Hoam Hall 4F-12, Youxi Zhang)
- Decentralized claims processing

(Day 2 Wed. 9:00am Hoam Hall 4F-07, Runhuan Feng)

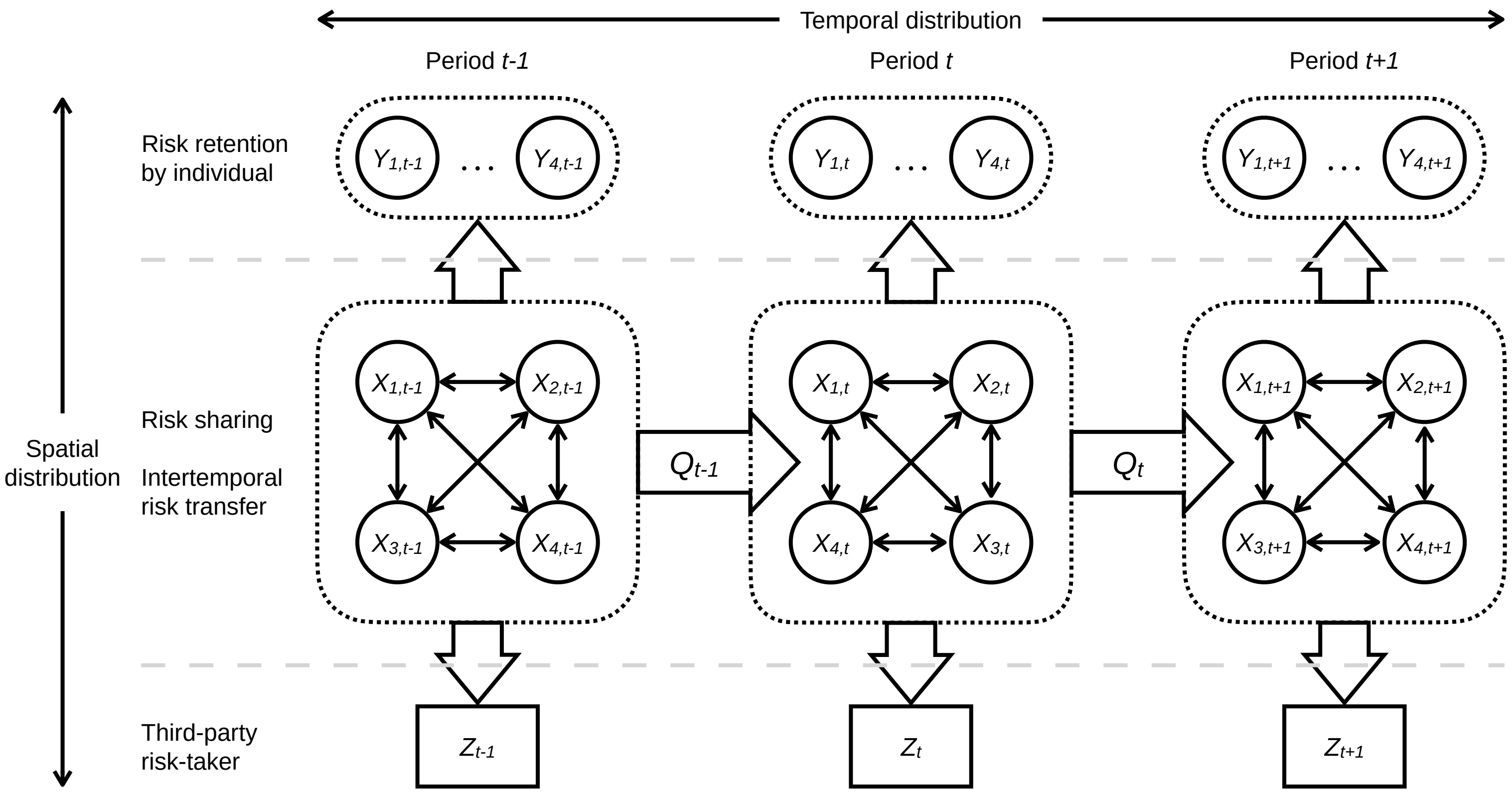


Decentralized Finance



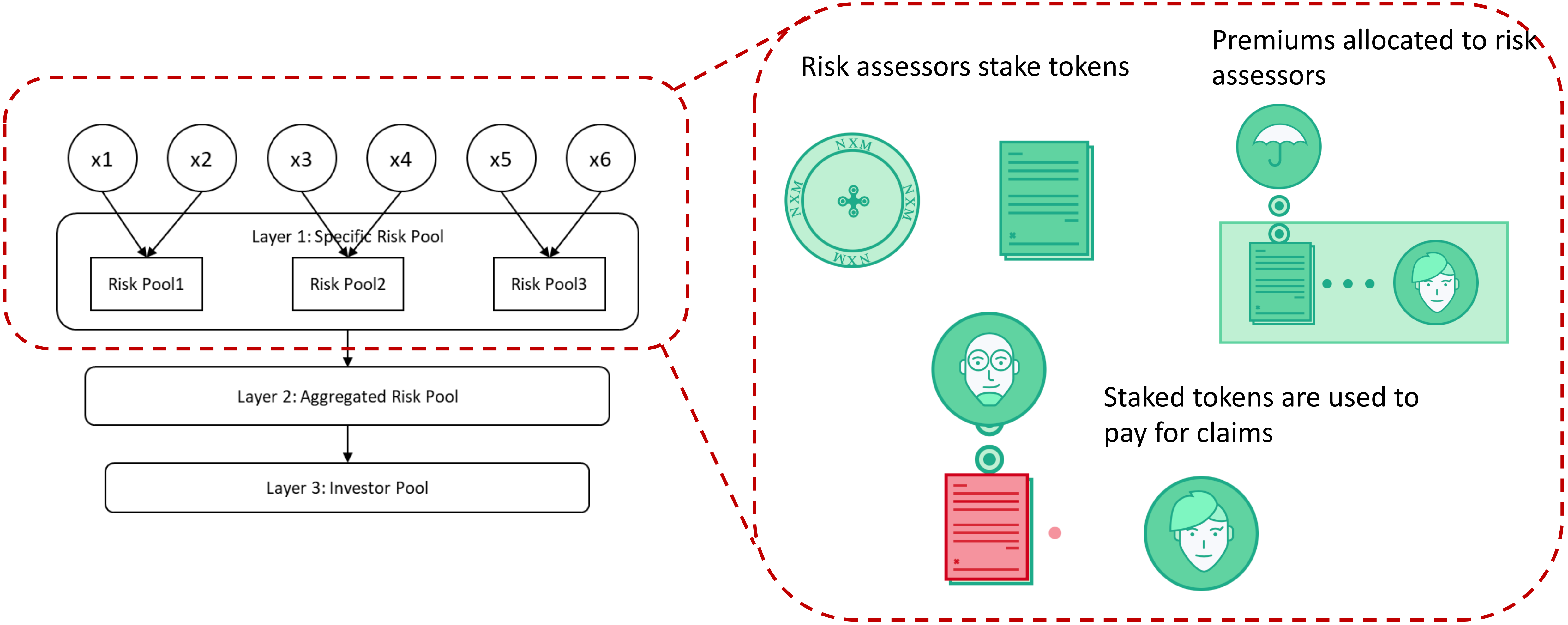


Spatio-Temporal Risk Sharing



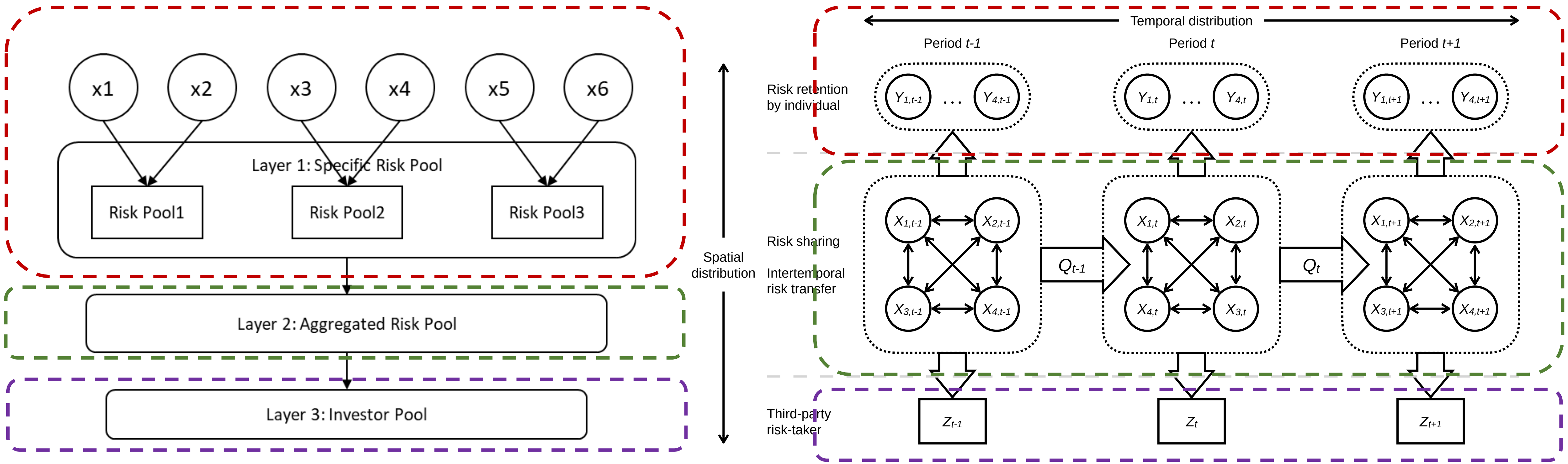
Feng, R., & Liu, P. (2025). Spatio-temporal risk sharing and transfer: A unified theory of multi-period decentralized insurances and annuities. *Journal of Risk and Insurance*.

Tokenomics of DeFi Insurance



Feng, R., Wu, Y., Jing, X. & Wu, Z. (2026). Tokenomics of DeFi insurance: a multi-layer risk sharing framework. Arxiv

Tokenomics of DeFi Insurance



Structural Comparison

Table 5: Actuarially Fair Risk Sharing via Different Layer Models

Business Model	Premium Distribution (%)			Claim Allocation (%)			Return (SD) (%)			Sharpe Ratio			Ruin Probability (%)	VaR_{95}(%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	$L^{(1)}$	$L^{(2)}$	$L^{(3)}$	$L^{(1)}$	$L^{(2)}$	$L^{(3)}$	$L^{(1)}$	$L^{(2)}$	$L^{(3)}$	$L^{(1)}$	$L^{(2)}$	$L^{(3)}$	$L^{(3)}$	$L^{(3)}$
Panel A: Baseline Setting														
L^*_{123}	75.84	22.95	1.21	75.83	22.17	2.00	0.01 (0.09)	-0.01 (19.69)	-0.14 (6.89)	0.11	0.00	-0.02	1.40	61.71
L^*_{13}	75.84	-	24.16	75.83	-	24.17	0.01 (0.09)	-	0.00 (2.97)	0.11	-	0.00	0.24	51.17
L^*_{12}	75.84	24.16	-	75.83	24.17	-	0.01 (0.09)	0.00 (2.97)	-	0.11	0.00	-	0.24	51.17
L^*_{23}	-	96.27	3.73	-	88.49	11.51	-	-0.43 (26.06)	-0.64 (34.00)	-	-0.02	-0.02	22.96	100
Panel B: Extended Setting														
L^*_{123}	75.84	22.95	1.21	75.83	23.16	1.00	15.18 (0.09)	1.25 (12.64)	2.78 (1.66)	173.35	0.1	1.67	0.08	-55.01
L^*_{13}	75.84	-	24.16	75.83	-	24.17	15.18 (0.09)	-	2.38 (0.75)	173.35	-	3.19	0.00	-33.02
L^*_{12}	75.84	24.16	-	75.83	24.17	-	15.18 (0.09)	2.38 (0.75)	-	173.35	3.19	-	0.00	-33.02
L^*_{23}	-	96.27	3.73	-	98.78	1.22	-	2.81 (5.55)	3.6 (5.77)	-	0.51	0.62	1.17	-103.49
Panel C: Extended Setting—After 30 Periods of Accumulation														
L^*_{123}	75.84	22.95	1.21	75.83	23.82	0.35	15.18 (0.09)	0.83 (8.75)	3.10 (0.80)	173.35	0.10	3.86	0.01	-112.49

Testing of Existing Business Models

Table 6: Practical Risk Sharing via Different Layer Structures

Business Model	Premium Distribution (%)			Claim Allocation (%)			Return (SD) (%)			Sharpe Ratio			Ruin Probability (%)	VaR_{95}(%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	$L^{(1)}$	$L^{(2)}$	$L^{(3)}$	$L^{(1)}$	$L^{(2)}$	$L^{(3)}$	$L^{(1)}$	$L^{(2)}$	$L^{(3)}$	$L^{(1)}$	$L^{(2)}$	$L^{(3)}$	$L^{(3)}$	$L^{(3)}$
Panel A: Baseline Setting														
Nexus Mutual	50	-	50	49.96	-	50.04	0.07 (0.06)	-	0.00 (6.28)	1.14	-	0.00	1.27	66.49
Bridge Mutual	80	20	-	80.02	19.98	-	0.01 (0.09)	0.00 (2.15	-	0.14	0.00	-	0.11	47.05
Unslashed	100	-	-	99.62	-	-	0.14 (0.07)	-	-	2.03	-	-	-	-
InsurAce	-	1	0	-	92.02	7.98	-	0.37 (20.66)	-0.96 (38.24)	-	0.02	-0.03	17.99	100
InsurDEFI	-	50	50	-	26.99	73.01	-	-12.37 (40.21)	-4.55 (47.31)	-	-0.31	-0.10	65.36	100
Nsure	50	50	0	49.96	44.48	5.25	0.07 (0.06)	0.68 (22.35)	-0.91 (31.89)	1.14	0.03	-0.03	11.66	100
Panel B: Extended Setting														
Nexus Mutual	50	-	50	49.96	-	50.04	18.07 (0.06)	-	2.80 (1.15)	295.29	-	2.44	0.02	-39.16
Bridge Mutual	80	20	-	80.02	19.98	-	14.49 (0.09)	2.31 (0.69)	-	159.73	3.35	-	0.00	-34.34
Unslashed	100	-	-	99.62	-	-	7.75 (0.07)	-	-	108.96	-	-	-	-
InsurAce	-	1	0	-	99.33	0.67	-	3.32 (3.66)	3.32 (4.13)	-	0.91	0.80	0.77	-116.75
InsurDEFI	-	50	50	-	35.57	64.43	-	-10.32 (44.38)	2.44 (22.64)	-	-0.23	0.11	8.9	100
Nsure	50	50	0	49.96	48.31	1.73	18.07 (0.06)	2.69 (9.82)	2.73 (6.29)	295.29	0.27	0.43	1.27	-3.84

Thank you for listening!

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Monopoly Pricing of Weather Index Insurance

Tim J. Boonen Wenyuan Li Zixiao Quan
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June 29, 2026

香 港 大 學
THE UNIVERSITY OF HONG KONG

2026 International Workshop on Risk and Insurance

Outline

Motivation: Weather Risks & Index Insurance

- **Agricultural Vulnerability:** Weather-based risks severely threaten agricultural livelihoods and the socioeconomic stability of rural communities.
- **Traditional Indemnity Insurance:** Widely adopted but suffers from high administrative costs, moral hazard, and relies heavily on subjective loss assessments.
- **Index Insurance:**
  - Connects payoffs to objective, verifiable weather indices.
  - Mitigates moral hazard and lowers transaction costs.
- **The Core Challenge:** Designing contracts that materially hedge farmer risk (minimizing *basis risk*) while remaining profitable. Especially in presence of high-dimensional and nonlinear weather-yield relationships as for weather index insurance.

Our Contributions

- **Game-Theoretic Framework:** We model monopoly pricing as a Bowley-type sequential game (Insurer as leader, Farmer as follower).
- **Deep Learning Architectures:** We compare Fully Connected Neural Networks (NNs) with Convolutional Neural Networks (CNNs) for modeling index payoffs, which demonstrates how CNNs efficiently reduce basis risk.
- **Pricing Flexibility:** We analyze three premium strategies:
    1. Single risk-loading expected premium.
    2. Two-parameter distortion premium.
    3. Fully flexible pricing kernel.
- **Algorithmic Innovation:** We solve the game using a penalized bilevel programming algorithm with a function-value-gap penalty, which requires no strong convexity assumptions on the lower level.

Literature Review: Bowley Solutions in Insurance

- **Monopoly Pricing:** Typically modeled as a leader-follower game where the insurer sets premiums and the policyholder chooses optimal coverage (Chan and Gerber, 1985).
- **Research Gap:** The current Bowley literature focuses almost exclusively on *indemnity* insurance contracts written on actual incurred losses.
- **Our Extension:** We apply Bowley equilibrium concepts specifically to the design and pricing of *weather index* insurance in concentrated markets.

Literature Review: Index Insurance & Basis Risk

- **Nonlinear Relationships:** Weather-yield relationships are highly complex. Flexible models like B-splines (Tan and Zhang, 2024) and standard Neural Networks (Chen et al., 2024) have been proposed to align payoffs and reduce basis risk.
- **Methodological Gap:** While standard NNs improve upon linear models, they require flattening 2D weather-time matrices. This destroys the structural context of the weather.
- **Our Extension:** We introduce CNNs to directly process the index-time matrix as an “image“, which captures hierarchical, localized weather patterns to further minimize basis risk (Krizhevsky et al., 2012; Chen et al., 2024).

Sequential Game Formulation

- **The Farmer (Follower):** Faces a stochastic production loss Y. Chooses insurance payoff function $I(\mathbf{X})$ to minimize a distortion risk measure ρ_F.
- **The Insurer (Leader):** Anticipates farmer's best response. Chooses premium principle parameters to maximize profit net of administrative costs μ.

Upper Problem (UP): Insurer

$$\max_{\Pi \in \mathcal{P}_s} \Pi(I(\mathbf{X})) - (1+\mu)\mathbb{E}(I(\mathbf{X}))$$

Lower Problem (LP): Farmer

$$\min_{I \in \mathcal{I}} \rho_F(Y - I(\mathbf{X}) + \Pi(I(\mathbf{X})))$$

$$\text{s.t.} \quad I(\mathbf{X}) \geq 0$$

Distortion Risk Measures

Both parties evaluate risks using distortion functions $g : [0, 1] \to \mathbb{R}_+$.

Farmer's Preferences (ρ_F):

- *Conditional Value-at-Risk (CVaR):* Focuses on tail risk. $g(s) = \min\{\frac{s}{1-\alpha}, 1\}$.
- *Convex Combination:* Balances CVaR and expected risk.

$$g_f(s) = \lambda s + (1 - \lambda) \min \left\{ \frac{s}{1-\alpha}, 1 \right\}$$

Insurer's Premium Principles (Π):

- **Problem 1 ($\mathcal{P}_{s1}$):** Expected premium with loading θ.
- **Problem 2 ($\mathcal{P}_{s2}$):** Power distortion premium (parameters θ, ρ).
- **Problem 3 ($\mathcal{P}_s$):** Fully flexible pricing kernel g_i.

Data Overview

- **Yield Data:** Annual county-level soybean data for Iowa (NASS), covering 1940-2023. Normalized and detrended to extract pure weather-induced production losses.
- **Weather Data:** High-dimensional PRISM Climate Group data.
- 7 climatic indices $\times$ 12 months = 84-dimensional grid.

Variable	Description
pcpnk	Total precipitation (rain and melted snow)
tmaxk	Daily maximum temperature
tmink	Daily minimum temperature
dptk	Daily mean dew point temperature
vpdmaxk	Daily maximum vapor pressure deficit
vpdmink	Daily minimum vapor pressure deficit

Neural Network Models (NN vs. CNN)

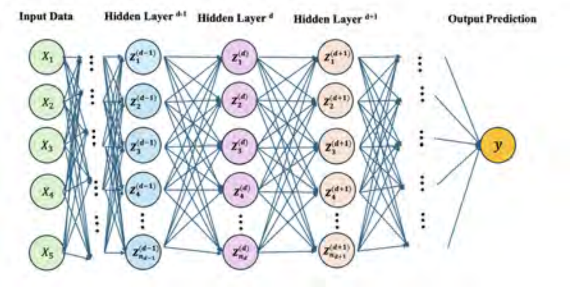


Figure 1: Traditional Fully Connected Neural Network (NN)

- **Limitation:** NNs require flattening the 2D weather-time matrix, which destroys the structural, spatial-temporal relationships of weather patterns.

Convolutional Neural Networks (CNNs)

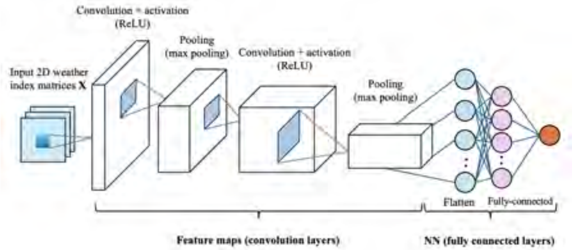


Figure 2: Convolutional Neural Network (CNN) Structure

- **Advantage:** Treats the index-time matrix as an “image.”
- Uses convolutional kernels to extract local features hierarchically.
- Weight sharing makes the model robust to shifts, which reduces overfitting.

Bilevel Programming Challenges

The generic bilevel problem is:

$$\mathcal{BP} : \min_{x,y} f(x,y) \text{ s.t. } x \in \mathcal{C}, y \in \mathcal{S}(x) := \arg\min_{y \in \mathcal{U}(x)} h(x,y) \tag{1}$$

The Challenge:

- The upper problem relies precisely on the solution set $\mathcal{S}(x)$ of the lower problem.
- Because our lower-level objective $h(x,y)$ (farmer's CVaR) is a linear function of order statistics, it is polyhedral and convex, but **not strongly convex**.
- Traditional implicit gradient methods fail here.

Value-Gap Penalty Reformulation

We transform the nested problem into a single-level problem by introducing a penalty $p(x, y)$:

$$\mathcal{BP}_{\gamma p} : \min_{x,y} F_{\gamma}(x, y) = f(x, y) + \gamma p(x, y) \text{ s.t. } x \in \mathcal{C}, y \in \mathcal{U}(x) \qquad (2)$$

Function-Value-Gap Penalty:

$$p(x, y) = h(x, y) - v(x), \quad \text{where } v(x) := \min_{y' \in \mathcal{U}(x)} h(x, y')$$

- Because $h(x, \cdot)$ satisfies a *weak sharp minimum* on compact sets, this penalty acts as a valid squared-distance bound.
- By applying **Danskin's Theorem**, we can approximate the subgradient of the value function $\nabla v(x)$ using any optimal lower-level solution y^*.

Algorithm: PBGD Implementation

Algorithm 1 PBGD for Expected Premium

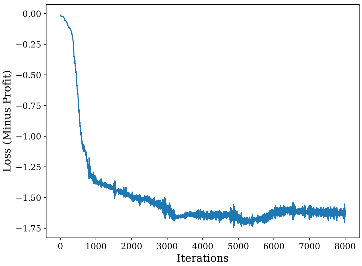
Input: Neural networks θ_{nn}, $\hat{I}^{\theta}_{nn}$, I^{θ}_{nn}; parameters $\alpha_0, \lambda, \gamma, \mu, N_L, N_C$.
for each iteration $n_C = 1, \dots, N_C$ **do**
    for each LP objective iteration $n_L = 1, \dots, N_L$ **do**
        Assign weights $I^{\theta}_{nn} \to \hat{I}^{\theta}_{nn}$; Compute step size $\alpha^{(L)}_{n_L}$;
        Update $\hat{I}^{\theta}_{nn}$ by gradient descent on the LP objective.
    end for
    Compute $\mathrm{LP}(\hat{I}^{\theta}(\mathbf{X}))$ using $\hat{I}^{\theta}_{nn}$;
    Compute penalty $\gamma \cdot \left(\mathrm{LP}(I^{\theta}(\mathbf{X})) - \mathrm{LP}(\hat{I}^{\theta}(\mathbf{X}))\right)$;
    Compute combined objective:

$$-\left(\Pi(I^{\theta}(\mathbf{X})) - (1+\mu)\mathbb{E}(I^{\theta}(\mathbf{X}))\right) + \gamma \cdot \left(\mathrm{LP}(I^{\theta}(\mathbf{X})) - \mathrm{LP}(\hat{I}^{\theta}(\mathbf{X}))\right)$$

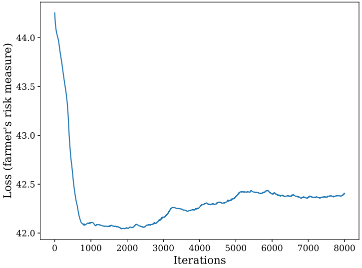
    Update θ_{nn} and I^{θ}_{nn} by gradient descent on combined objective.
end for
Output: Optimal θ and $I(\mathbf{X})$.

Problem 1: Training Convergence (NN, Convex Combo)

Farmer's risk measure: $g_f(s) = 0.5s + 0.5\min\left\{\frac{s}{1-0.8}, 1\right\}$



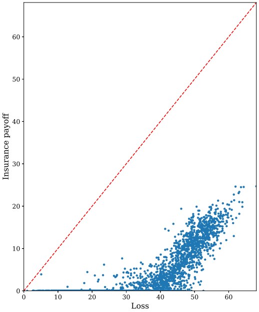
(a) Upper-problem loss (Negative Profit)



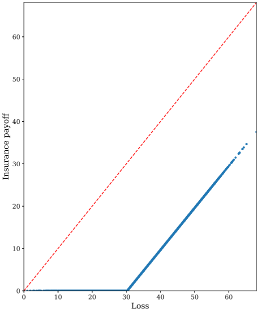
(b) Lower-problem loss (Farmer's Risk)

Key Insight: Loss curves stabilize indicates convergence to an equilibrium.

Problem 1: Payoff Comparison (Convex Combo $\lambda = 0.5$)



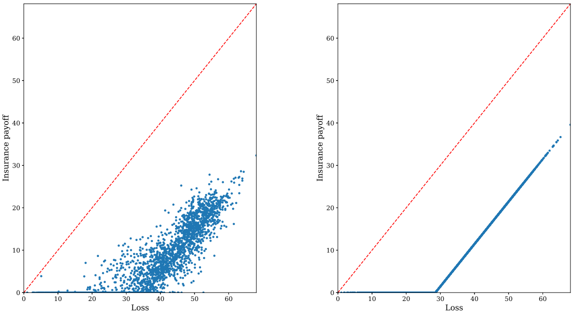
(a) Index Insurance



(b) Indemnity Insurance

Key Insight: Optimal policies exhibit stop-loss shapes. Index insurance ($\theta^* = 0.4130$) contains significant scatter noise compared to the pure Indemnity baseline ($\theta^* = 0.2812$).

Problem 1: Payoff Comparison (Pure CVaR)

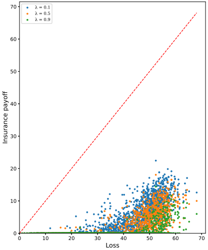


(a) Index Insurance (b) Indemnity Insurance

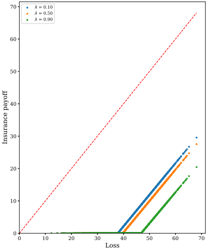
Key Insight: When the farmer acts strictly on CVaR, the stop-loss shape persists, but the insurer applies a much higher risk loading for Index insurance ($\theta^* = 0.5500$) compared to Indemnity insurance ($\theta^* = 0.4853$).

Problem 1: Sensitivity Analysis (Varying λ)

Farmer's Risk Aversion varies: $\lambda = 0.1, 0.5, 0.9$



(a) Index Insurance



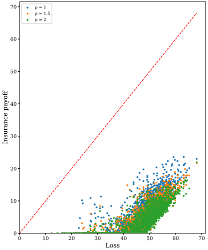
(b) Indemnity Insurance

λ	**0.1**	**0.5**	**0.9**
Index θ^*	0.7542	0.5578	0.3068
Indemnity θ^*	0.6451	0.3724	0.2591

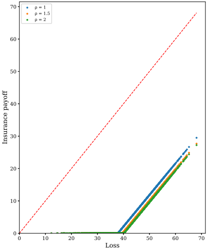
Key Insight: Higher λ (less risk-averse) leads to higher deductibles and lower optimal risk loading (θ^*).

Problem 1: Sensitivity Analysis (Varying ρ)

Insurer's Premium Distortion varies: $\rho = 1.0, 1.5, 2.0$



(a) Index Insurance

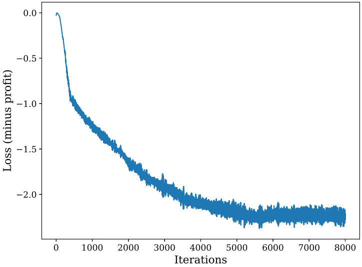


(b) Indemnity Insurance

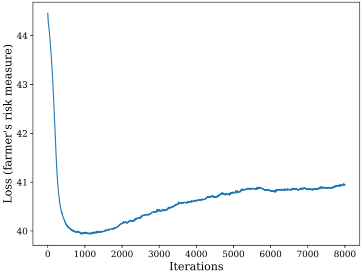
ρ	**1.0**	**1.5**	**2.0**
Index θ^*	1.0181	1.0333	1.0802
Indemnity θ^*	0.8796	0.9382	0.9855

Key Insight: A larger ρ (heavier tail loading by the insurer) slightly raises the deductibles for the farmer and increases the risk loading θ^*.

Problem 1: CNN Training Convergence



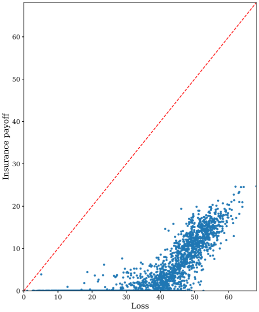
(a) UP Loss (Negative Profit)



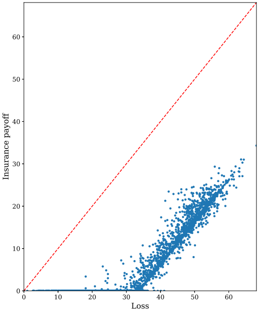
(b) LP Loss (Farmer's Risk)

Key Insight: Using CNNs to model the payoff yields a smoother and more robust training convergence pattern.

Problem 1: Payoff Modeling (Combo: NN vs. CNN)



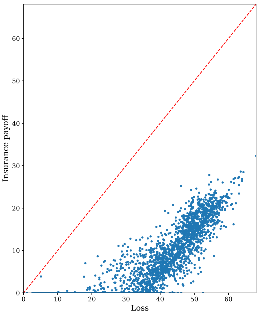
(a) NN: Index (Combo)



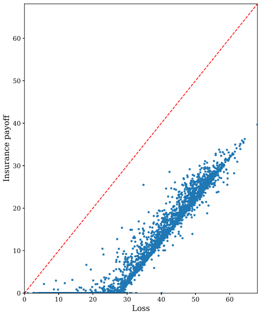
(b) CNN: Index (Combo)

- **Noise Reduction:** CNNs capture the spatial-temporal weather grids accurately, which visually removes the scattered basis risk seen in standard NNs.

Problem 1: Payoff Modeling (CVaR: NN vs. CNN)



(a) NN: Index (Pure CVaR)

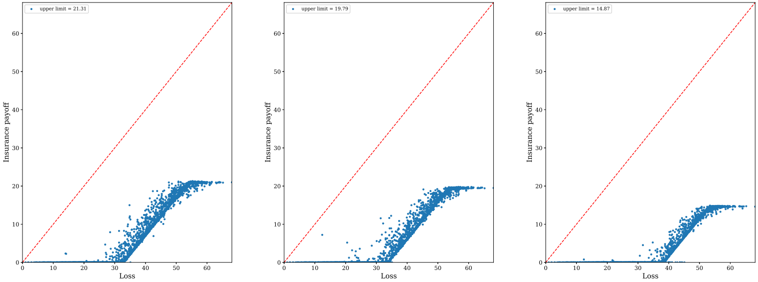


(b) CNN: Index (Pure CVaR)

- **Profit Maximization:** By reducing the basis risk seen on the left, our CNN models pushed the index profit up to 4.07—significantly closer to the theoretical pure indemnity maximum of 4.82.

Problem 2: Two-Parameter Premium (Index)

Insurer optimizes both θ and ρ. Farmer uses convex combination (λ).

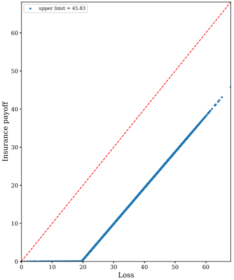


(a) $\lambda = 0.1$ ($\theta^* = 0.2237, \rho^* = 2.0644$)
(b) $\lambda = 0.5$ ($\theta^* = 0.0758, \rho^* = 1.7341$)
(c) $\lambda = 0.7$ ($\theta^* = 0.0190, \rho^* = 1.5016$)

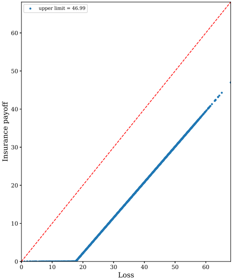
Key Insight: Extra pricing power creates a “limited stop-loss” shape (deductible + maximum cap). As the farmer becomes more risk-averse (lower λ), the insurer extracts more profit via higher θ and ρ.

Problem 2: Two-Parameter Premium (Indemnity)

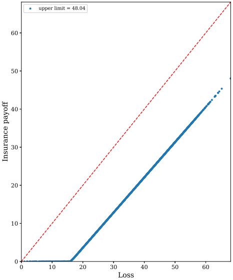
Theoretical baseline for the same parameters.



(a) $\lambda = 0.1$ $(\theta^* = 0.2761, \rho^* = 1.7078)$



(b) $\lambda = 0.5$ $(\theta^* = 0.1022, \rho^* = 1.5641)$

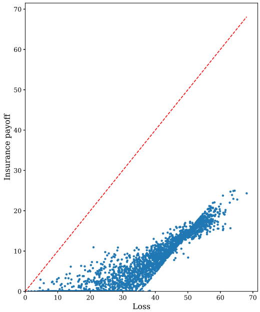


(c) $\lambda = 0.7$ $(\theta^* = 0.0258, \rho^* = 1.4565)$

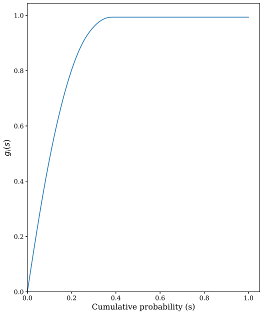
Key Insight: The indemnity counterpart maintains the clean, theoretical limited stop-loss shape. This allows the insurer to achieve slightly higher absolute profit ceilings.

Problem 3: Fully Flexible Pricing Kernel (Index)

The insurer uses a neural network to model $g_i(s)$ with total flexibility.



(a) Index Payoff

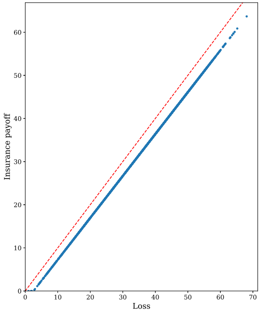


(b) Index Kernel $g_i(s)$

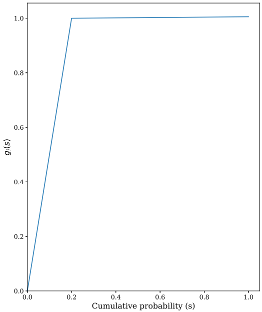
Key Insight: Given complete pricing flexibility, the optimal kernel is smooth and concave. The monopolistic insurer extracts an expected profit of **8.7961**—more than double the single-parameter model.

Problem 3: Fully Flexible Pricing Kernel (Indemnity)

Theoretical baseline under a flexible pricing kernel.



(a) Indemnity Payoff



(b) Indemnity Kernel $g_i(s)$

Key Insight: Interestingly, for pure indemnity, the optimal pricing kernel is piecewise linear with a kink at $s = 0.2$. This drives the deductible close to zero, which yields a theoretical profit of **17.2982**.

Conclusions

- **Architectural Impact:** Convolutional Neural Networks (CNNs) are highly effective at processing spatial-temporal weather grids. They yield significantly smoother, more robust payoff functions, systematically reducing basis risk compared to fully connected NNs.
- **Market Dynamics:** In concentrated markets, a monopolistic insurer effectively exploits farmer risk aversion. We demonstrated that granting the insurer greater pricing flexibility (from a scalar loading, to two parameters, to a full kernel) directly correlates with aggressive profit extraction.
- **Methodological Advance:** Our function-value-gap penalized bilevel programming algorithm scales successfully to large weather-yield datasets. It effectively solves sequential games without requiring strict strong convexity on the lower-level problem.

Thank you!

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