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Chapter 10: Governance, Ethics, and the Future of Autonomous Insurance Intelligence Systems

10.1. Introduction

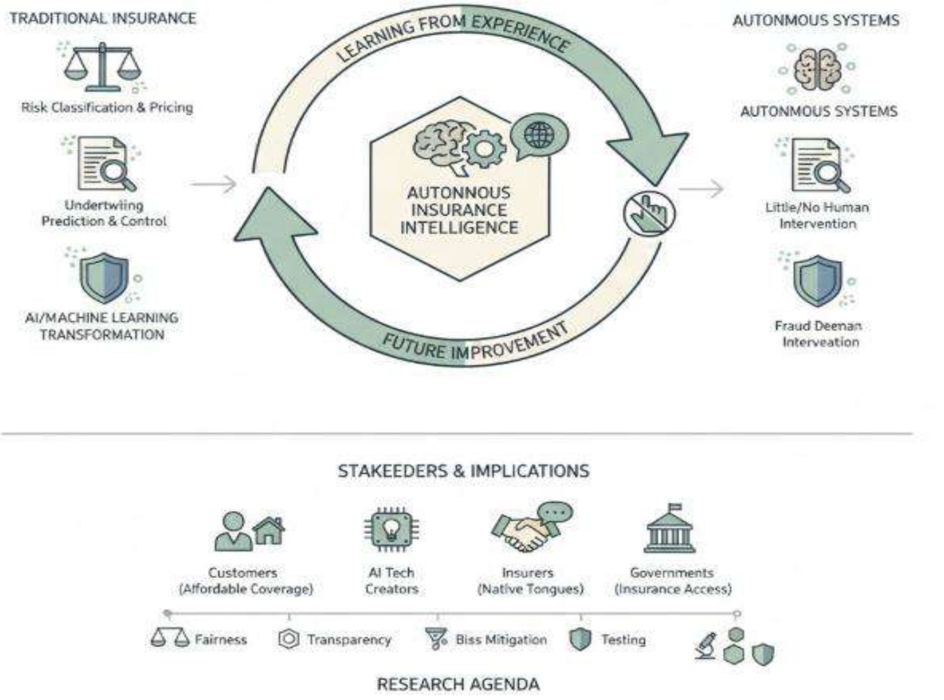
Autonomous Insurance Intelligence systems utilize Artificial Intelligence and Machine Learning technologies to independently complete insurance tasks historically performed by humans. Put simply, they are primarily computer-based service providers which essentially rely on the insurance business model to create profit. These systems may perform any task in the insurance value chain including, but not limited to: product development, pricing, risk selection, underwriting, policy administration, reinsurance, fraud detection, and claims management. Although tasks in specific insurance business areas can be semantically considered as autonomous, and may technically only require automation, systems utilizing these technologies are nonetheless classified as Autonomous Insurance Intelligence systems if their application enables them to operate across multiple areas within the value chain. Stakeholders consist of the insurance incumbents and new entrants who have the intention to implement, or are in the process of implementing, Autonomous Insurance Intelligence systems.

The motivation for this research stems from the fact that Autonomous Insurance Intelligence represents the next frontier in the evolution of Artificial Intelligence and Machine Learning technologies in the insurance industry. Awareness of and interest in their strategic possibilities has risen significantly throughout 2020. The objective is to facilitate the novel research field by providing the necessary insights, identifying the critical issues that need shadowing, and mapping future research avenues. Key terms include Autonomous Agents, Autonomous Systems, Insurance Intelligence, Machine Learning, and System Autonomy. It is also important to note that research in the area is ongoing. Therefore, the information presented is indicative rather than exhaustive.

10.1.1. Overview of Autonomous Insurance Intelligence

The proposition of autonomous insurance intelligence defined here consists of insurance products, services, systems, operations, and delivery channels using AI software or technological capability that can learn from experience for future improvement without human steering or interaction. Such systems relay messages to consumers using insurance terms in their native tongues. Stakeholders include customers seeking affordable coverage, AI technology creators, insurers serving customers in their native tongues, and governments interested in promoting insurance access. Despite being in a relatively early stage of commercialisation compared with financial services, researchers expect implications for the insurance industry's business models, pricing, and the servicing of clients. The proposed research agenda addresses fairness, transparency, bias mitigation, consumer protection, and testing.

With the adoption of genuine AI or machine learning for predictive and prescriptive decision-making, traditional insurance processes of risk classification, pricing, underwriting, claims prediction, settlement, fraud detection, and control are mainly developing into autonomous systems that require little or no human intervention. Simple routines that do not actively learn (for example, automated fraud detection flagging transactions for human investigation) are not included.


TRADITIONAL INSURANCE
Risk Classification & Pricing
Undertwiing Prediction & Control
AI/MACHINE LEARNING TRANSFORMATION
LEARNING FROM EXPERIENCE
AUTONNOUS INSURANCE INTELLIGENCE
FUTURE IMPROVEMENT
AUTONMOUS SYSTEMS
AUTONMOUS SYSTEMS
Little/No Human Intervention
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STAKEEDERS & IMPLICATIONS
Customers (Affordable Coverage)
AI Tech Creators
Insurers (Native Tongues)
Governments (Insurance Access)
Fairness
Transparency
Biss Mitigation
Testing
RESEARCH AGENDA

Fig 10.1: Autonomous Insurance Intelligence: A Research Agenda for Self-Learning Systems, Ethical Governance, and Multilingual Inclusion

10.2. Foundations of Autonomous Insurance Intelligence

Autonomous Insurance Intelligence (AAI) comprises artificial intelligence-enabled decision-making systems that support, substitute, or automate the risk transformation and management activities of insurance core sectors, departments, and functions. These algorithms use a combination of inputs from structured and unstructured data sources, are deployed in risk-sensitive settings, and have the potential to learn from experience. Hence, the decisions of these systems may evolve as they process novel data inputs, act on past choices, and incorporate feedback from users and the external environment. Assuming that the domains of decision-making are sufficiently defined and bounded, and that the systems are properly validated, accurate and reliable decisions may be expected.

While relevant AI systems may help insurance enterprises operate with additional efficiency, reduce errors, and discover new opportunities, financial institutions must deploy them with care. Autonomous systems should be of higher decision quality than earlier human-driven operations. Even if an incumbent is the first to deploy such systems in the marketplace, it may not be the first mover. Firms seeking to enter the market with a radically new approach based on such systems must carry out additional due diligence and apply for sandbox testing.

The related research question maps the potential impacts of the operation of autonomous insurance intelligence on the insurance marketplace, especially on competition among incumbents, new entrants, and adjacent players. Specific topics of interest include the likely reaction of incumbents with the scale and resources to seek similar efficiency gains or technical improvements, and whether the associated improvements will lead to price reductions that attract new consumers, create a wider base across the risks offered by the market, and/or encourage the entry of new competitors.

10.2.1. Core Concepts of Autonomous Insurance Intelligence

The term autonomous insurance intelligence system encompasses a diverse range of computer systems capable of making decisions and/or taking actions in the insurance domain that can be specifically construed as autonomous. Such software could include examination systems that analyse claims records and/or call centre recordings, prospective analysis systems that identify claims disclosure inconsistencies, underwriting systems with full application of the submitting party’s risk and solvency, decisioning systems that execute underwriting approvals or declinations, and localized or cross-global exposure and price-setting systems capable of offering quotes for reinsurance cover on any commercial risk.

Core definitions capture three key aspects: the algorithms, the data inputs, and the decision process. These groups determine whether a system is autonomous or simply advanced and at what level autonomy is engaged, from simple auto-decisioning—providing straightforward yes/no answers on agent-specific inquiries such as warranty compliance or direct insurance distribution channels—to full quantum mechanics-style modelling that calculates across vast sample spaces the full range of price versus exposure, binds the quote, and notifies the proposer via app and/or email, including payment capability.

10.3. Governance Frameworks for Autonomous Systems in Insurance

Applicable laws can be distinguished according to the form of risk exposure. Classifying involved systems by risk level–Thomas M. W. V. F. Dretzel et al. present a validated, publicly accessible, and continuously updated taxonomy of AI-enabled technology systems with potential for harm–supports deployment of corresponding compliance requirements and reduces regulatory burdens. Additionally, the moving nature of risk exposure is captured: for example, while liability towards insured cars and drones is typically on the manufacturers, custodian liability may shift towards users in guided operations, and negligent operational deployment may shift back to manufacturers. Where required, autonomous systems may be obliged to acquire operating licenses. The transfer of responsibility and associated obligations must also consider data processing operations: control over data flows, and thus accountability, shifts as in artificial intelligence operations, but is subject to protective mandates of the General Data Protection Regulation for sensitive personal data. Furthermore, since insurance service provisioning typically operates at a cross-border level–unlike the domestic-level operations of most other AI-related risk exposure–cross-border legal aspects, especially extraterritorial application of domestic laws and trade regulations, assume greater importance.

Enforcement of liability is founded upon audit-proof trail records to ascertain causality. Regulation of insurance-based autonomous systems for public safety thus requires practical definition of supervisory instruments, operational safeguards, comprehensive responsibility-sharing agreements, grievance redress mechanisms to prevent lapses and misconduct in overall safety, procedures for incident management, and continuity provisions for the operation and delivery of services.

10.3.1. Legal and Regulatory Considerations

The governance of Autonomous Insurance Intelligence (AAI) systems requires an understanding of the existing laws and regulations that are applicable to their activities in order to make certain that the systems operate legally. The activities of the AAI systems in the insurance market are wide-ranging and may expose the insurance market to different types of risk due to the use of these systems. Because of this exposure, and depending on the risk associated with the different types of activities, different legal rules will be applicable. The applicable laws can be grouped into three categories: general laws applicable to any business entity, specific laws addressing the risk posed by the business, and laws applicable to the sharing of personal data between different stakeholders.

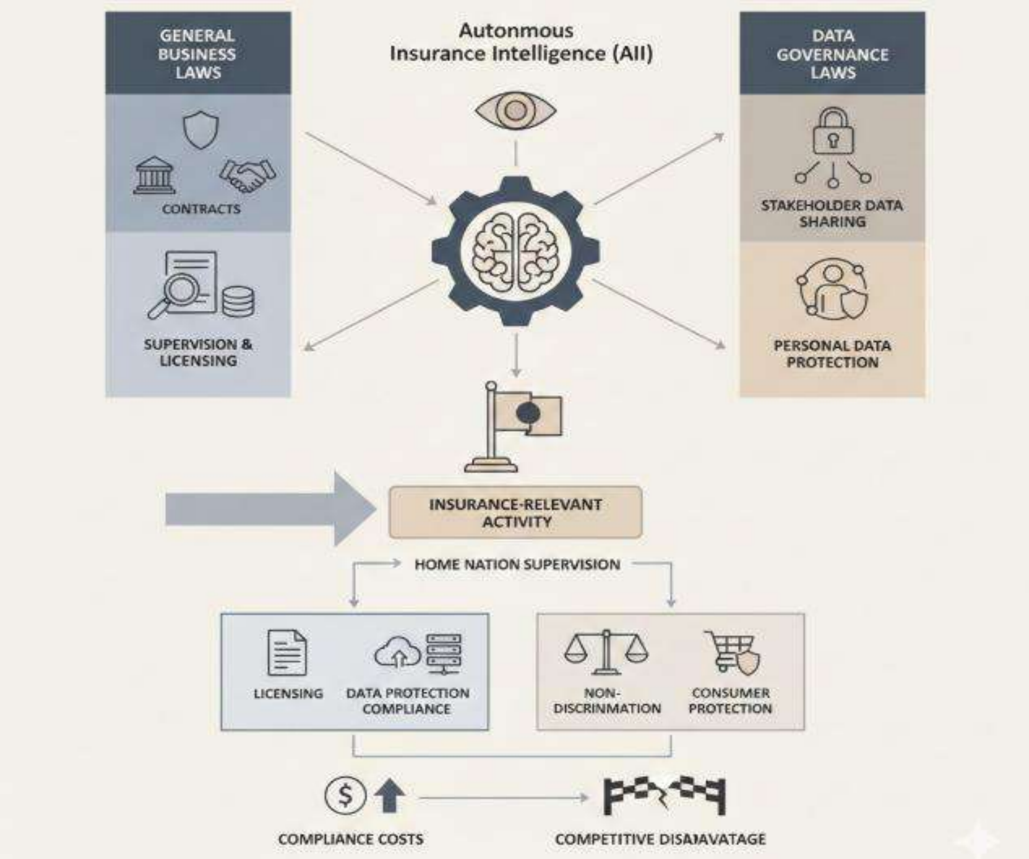

Fig 10.2: Regulatory Architectures and Risk-Tiered Governance for Autonomous Insurance Intelligence (AII) Systems

The functioning of an AAI system in the insurance market is similar to that of a traditional insurer incumbent with respect to third-party insurance contracts. This means that the major activity of the AAI system can be classified as an insurance-relevant activity exposed to the supervision of the insurance authorities and the corresponding supervision in its home nation. Because of this supervision, it needs to comply with existing laws, including laws about licensing, protection of personal data, and the infrastructure supporting the insurance activity. Besides these laws, the activities will also be exposed indirectly to laws in areas of non-discrimination and consumer protection. These regulations might put other non-AI insurance systems at a competitive disadvantage and entail higher costs for the customer.

10.3.2. Oversight Mechanisms and Accountability

Oversight consists of independent review and monitoring of the systems by experts or knowledgeable third parties who possess no vested interests in any aspect of the autonomous systems. The review process can be performed prior to deployment to suggest improvements, during execution and data collection and, occasionally, afterwards to better understand emergent behaviours. Audit trails must be established to keep track of the historical decisions made, the data exploited and periodically re-evaluated fairness results. These records assist in hands-on assessment by acknowledged external organizations without risk of bias. Governance bodies must be formed, composed of diverse stakeholders, comprising producers, customers, law experts, regulators, victims and serving societies. These actors share responsibilities in establishing the products, following their functioning, managing complaints, participating in the feedback cycle, and handling incidents.

Independent verification of incidents affecting any of the parties must be automated to the extent possible (e.g., contemporaneous audit by networked agents) and proactively encouraged. Events may require redress even if no fairness breach was detected, such as unjustified deaths. Accurate scapegoating must be avoided, assigning blame only to stakeholders responsible under normal conditions. The decision dependencies plus actor accountability must be fully co-explained, as well as any aspects that cannot. These explanations require enough nuances, detail and context for reassurance of all involved, especially when voters are kept uninformed to minimize manipulation opportunities.

10.4. Ethical Principles and Implications

Key ethical principles for the governance of autonomous intelligence systems in insurance engagement design are fairness and non-discrimination, transparency and explainability, and accountability. They are applicable to systems that collaterally enable economic discrimination or whose processes and results could be regarded, or interpreted by users, as discriminatory or unfair, even if were technically lawful. These principles only partly overlap with the legal requirements established under EU non-discrimination law, the GDPR, and the Digital Services Act.

Fairness and Non-Discrimination

To realize a fair and non-discriminatory use of autonomous systems in insurance services, fairness criteria must be clearly defined, potential sources of bias anticipated and mitigated, appropriate testing protocols designed and implemented, and any negative impact assessed on affected communities, notably vulnerable groups. These efforts require cooperation between insurers and public authorities: the former have the capabilities to advance fairness goals, while the latter are the rightful stakeholders to determine the nature and level of the fairness standard to be pursued.

Transparency and Explainability

Transparency and explainability requirements must account for the knowledge and competences of users with regard to the particular autonomous decision-making system on which an insurance service relies. As a minimum, certain guarantees and disclosures must in principle be provided always: users must know that an engagement is based on non-human decision-making and be able to access, in understandable terms, information about the precise provenance of the AI decision affecting them. Explainability must then be fulfilled for all decisions that fall within specific domains (critical or sensitive matters) and human decision-support systems. Finally, the natural limitation of any explanation must be candidly acknowledged.

10.4.1. Fairness and Non-Discrimination

A comparative law assessment of several jurisdictions reveals common legal obligations on fairness and non-discrimination that encompass the prevention of biased outcomes from AI-based systems, especially in high-risk applications. These obligations typically impose broad fairness duties, requiring firms to be proactive in understanding and controlling bias-propagating factors. Key sources of bias include biased training and historic data, proxy features that inadvertently reflect sensitive attributes, and biased users. Testing, auditing, and monitoring are established mitigation strategies, while the impact of AI on protected groups must be validated, using the precise population to which a fairness criterion applies. Although the law does not currently mandate explanations of AI decisions, users seek understandable justifications of decisions that impact them.

To support the integrity of the overall fairness-in-AI objective, the sector must address the digital divide to ensure all affected consumers can comprehend, interpret, and act upon notifications of explanations. Default options should offer greater protection, and biased user behavior should be countervailed. In addition, the AI systems deployed by the sector should not have individually biased impacts, even when they do not constitute an individual or group biasing course or a source of societal prejudice.

10.4.2. Transparency and Explainability

Autonomous models are sometimes labelled as “black-boxes,” because it is hard to establish their decision-making processes. In cases where discrimination is a concern, fairness services are required. It is important to ensure that the decisions of these models can be interpreted, but they do not need to be completely understood. On the user side, it is essential to have enough information and knowledge to use these tools properly; this requires some form of transparency. Users need to know the limitations of these tools, especially those related to the input data, since a change in the input data can completely change the performance of these models. The concept of explainability is completely different for a user sending a request to an NLP or other types of models for answer or completion and for an insurance company using or offering a service based on AI.

In the last case the company has to assure that the customer understands why an offer is being made. The customer-looking for a specific catastrophe insurance generically understands the offer, even if his/her knowledge is different from the specific insurance company language. An intermediary agent (broker or salesman) acting on behalf of the customer (on the customer side) must be able to explain in words understandable by his/her customer why the auto insurance offer is higher than others and the meta-agents offering qualified advices must justify any differences. On the insurance company side, it is necessary to provide information supporting the offer, like a rationale for the pricing, for the different coverage positions, etc.

10.5. Economic and Social Impacts

Market Competition and Innovation: Autonomous Insurance Intelligence (AII) may pose a challenge to legacy insurance models but should reduce entry barriers for AII-enabled start-ups and new insurance lines using alternative business models. Fulfilling this potential will require timely and efficient supervision to avert natural monopolies or oligopolies across critical segments. Marketplace competition should induce lower prices, at least for common risks that have digital models capable of winning business across different territories or for different parts of the world. These efficiency gains may spur dynamic competition if originality of setting and serving the AII can be turned into an asset that provides a sustainable edge. Where these factors are present, established companies should find it within their capabilities either to develop similar offers or to engage in partnerships in order to respond. Recent developments hint at the benefits of introducing a regulatory sandbox approach for AII in general.

Access, Inclusion, and Consumer Protection: A common concern is that, by reducing risks and simplifying processes, an increased use of AII acting as an insurance broker will lead to lower insurance prices and make more types of insurance available to more consumers. However, an opposite concern is that AII capitalising on endogenous talent will develop market power and raise prices. While upfront pricing of AI products should remain high, demand could concentrate in AII that match a user's language, cultural beliefs, etc., causing other AII companies to withdraw from the market. The demand for insurance products could also depend on other interactions, such as how attractive they are on social media. In fully digital markets, the risk of a digital divide may arise if AII systems provided by big corporations are not written in a language consumers understand, if the insurance products they predict are poorly explained, or simply if consumers lack the digital literacy needed to take advantage of these systems. Thus, a broader range of user and AII interactions and the motivation of users to understand their predictions could also benefit other areas of society.

10.5.1. Market Competition and Innovation

Autonomous insurance intelligence systems supported by upstream algorithmic risk models hold the potential to decrease insurance premiums and extend access to affordable products worldwide. While autonomous insurance intelligence may increase competition in insurance and help entrants penetrate markets faster, entry barriers remain considerable. Autonomous insurance modelling capabilities offer incumbents a first-mover advantage, enabling private system operators to exploit market timing, price, and service attribute-based competition to secure and maintain market leadership. Algorithms developed using a large volume of price-sensitive and service-sensitive data may allow market-dominating incumbents to reduce expected future claims and costs and make more trustworthy service and cost predictions than newly introduced systems.

Computer vision, natural language processing, and reinforcement learning enable companies to reduce operational costs, streamline processes, and improve premises security management. Processing delays for claim requests are shortened from an average of 15 days to one minute. Autonomous insurance capabilities may result in policy cost reduction of 30-40% and in dangerous working condition and high-risk investment domain cost reduction by 40-50%. Internal development of autonomous insurance systems may be unnecessary owing to the resources required. Existing capabilities in the digital insurance supply chain may also allow private companies to provide autonomous insurance products faster and at a lower cost than if developed independently. Global markets may benefit from adaptive regulation, with regulators acting as facilitators for testbed development.

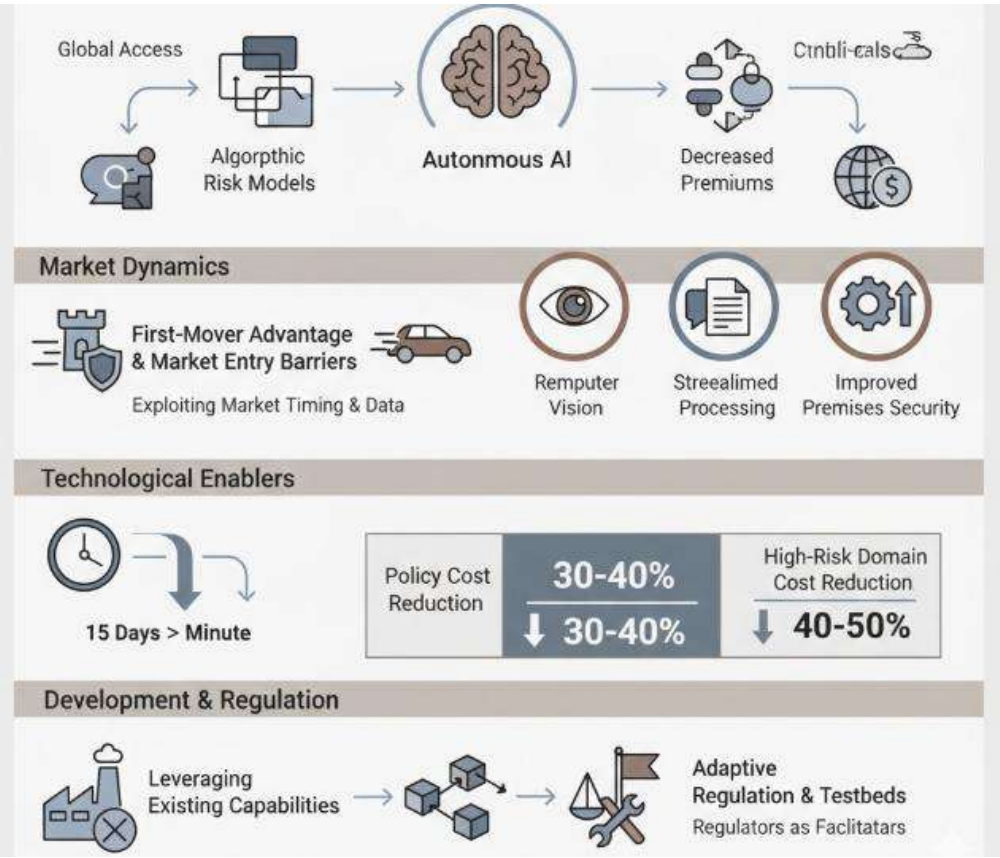

Fig 10.3: The Socio-Economic Impact of Autonomous Insurance Intelligence: Market Competition, Operational Efficiency, and the Role of Adaptive Regulation

10.5.2. Access, Inclusion, and Consumer Protection

The deployment of Autonomous Insurance Intelligence systems offers significant potential for making insurance more affordable and accessible. However, their uptake must also be assessed against the risks of exacerbating social disparities and disempowering vulnerable consumers. Several critical dimensions of access and protection emerge. First, while the use of AI systems to automate underwriting and claims decisions could improve the affordability of services for various kinds of policyholders, pricing effects remain ambiguous. For some applications, the use of AI is likely to lower costs and, hence, prices; for others, it may allow for a better matching of actual risk exposure with insurance pricing. Policyholders that might inadvertently benefit from overly generous terms may be economically exposed when claims exceed their expectations. The possibility for autonomous systems to make an insurance product more or less affordable than without such technology would then require economic analysis.

In turn, insurance is only a complementary element in the insurance protection that society offers. People exposed to the most significant social and economic difficulties do not have access to insurance, since it will be unaffordable. Society must provide those resources together with the schools, rehabilitation facilities, and any other necessary investments to mitigate the effects of extreme events. The economic resources of these vulnerable groups are so limited that the cost of any insurance policy is greater than the accident that occurs. Insurance, therefore, must be made accessible to all. The verticalization and modularization of insurance in combination with dynamic forms of pricing should allow insurers such as those in the travel sector to open insurance lines close to the accident that is being insured against effectively.

10.6. Technical Challenges and Standards

Section

1. Robustness, Reliability, and Safety: specify reliability targets, validation strategies, risk controls, failure modes, and safety certifications.

2. Interoperability and Standards: identify standardization needs, data schemas, interoperability protocols, and alignment with existing insurance tech ecosystems.

Technical and technological development of AI systems in insurance proceeds apace, but crucial foundations considerations for the design of monitoring, control, and quality-assurance mechanisms remain. Key high-level principles—such as fairness and non-discrimination, transparency and explainability, economic and social impact—serve to identify, delineate, and analyse a wide range of governance implications. These requirements are naturally elaborated into practical measures, policies, instruments, strategies, and methodologies that facilitate the development and deployment of Autonomous Insurance Intelligence systems in a manner that is trustworthy and aligned with society’s goals. However, meeting such principles continues to hinge on the resolution of critical technical and engineering challenges.

While these challenges differ in nature, they concern how well or poorly Autonomous Insurance Intelligence systems perform their designated tasks, and encompass, at least, issues related to their robustness, reliability, safety, interoperability, and standards. Inadequate quality in any of these dimensions threatens to compromise the very economic and social objectives that motivate the introduction of Autonomous Insurance Intelligence. For AII systems to provide societal benefits—with respect to affordability, inclusiveness, speed, and accuracy—work nonetheless often remains to be done.

10.6.1. Robustness, Reliability, and Safety

Reliability objectives for Autonomous insurance Intelligence systems must target the likelihood of safe–safe, safe–unsafe, unsafe–safe, and unsafe–unsafe interactions, with emphasis on catastrophic damages, complemented by risk controls that account for failure modalities and safety certification based on systemic validation. Systems provided directly by insurers or reinsurers will need to mitigate reasonably foreseeable harms on society users, while those from other parties to be used by insurers require proof of sufficient reliability.

Reliability is a high-level characteristic ascribed to a range of domains via various metrics or qualities and is important for many technologies, especially those involving Autonomous Intelligence. Nevertheless, given economic factors forcing greater reliance on full Automation and the societal expectations thereof, setting an explicit target robustness index is a necessary step for the industry. In the context of Autonomous Insurance Intelligence, reliability concerns notions of the likelihood of a safe operation or interaction, namely, the probabilities that a safety-critical system handled by other safety-critical systems behaves as expected:

A key challenge here is making sure that catastrophes do not happen more often than a reasonable threshold—that is, assessing the computation-intensive likelihoods of the aforementioned failure combinations capable of causing catastrophic damages. In practical terms, the problem can often be simplified by focusing on the likelihood of the one that leads to the most severe consequences.

10.6.2. Interoperability and Standards

Uniform standards for autonomous systems in insurance are not yet perceived as business necessities. Nevertheless, standardization is vital for market scalability, economic efficiency, and consumer protection. Several types of standardization will be needed: underlying data schemas to facilitate system interoperability; protocols for seamless, secure data sharing among insurance ecosystem partners; and organism-specific guidelines for complementing existing insurance technology standards and frameworks. Insurance sector regulators and supervisory authorities should initiate dialogue to address these needs.

Data-sharing protocols should balance data provider benefits with costs and risks borne by other ecosystem participants. Protocols might take the form of governance frameworks for trusted digital ecosystems in which participants share data under terms reflecting their contributions to other parties' products and services. Such consortia have emerged in sectors such as utilities and identity management. Bias and fairness issues can attract scrutiny from non-economic stakeholders, including regulators, community groups, and civil society. Addressing those issues proactively and transparently can mitigate the operational and reputational risks of unfair or biased market practices.

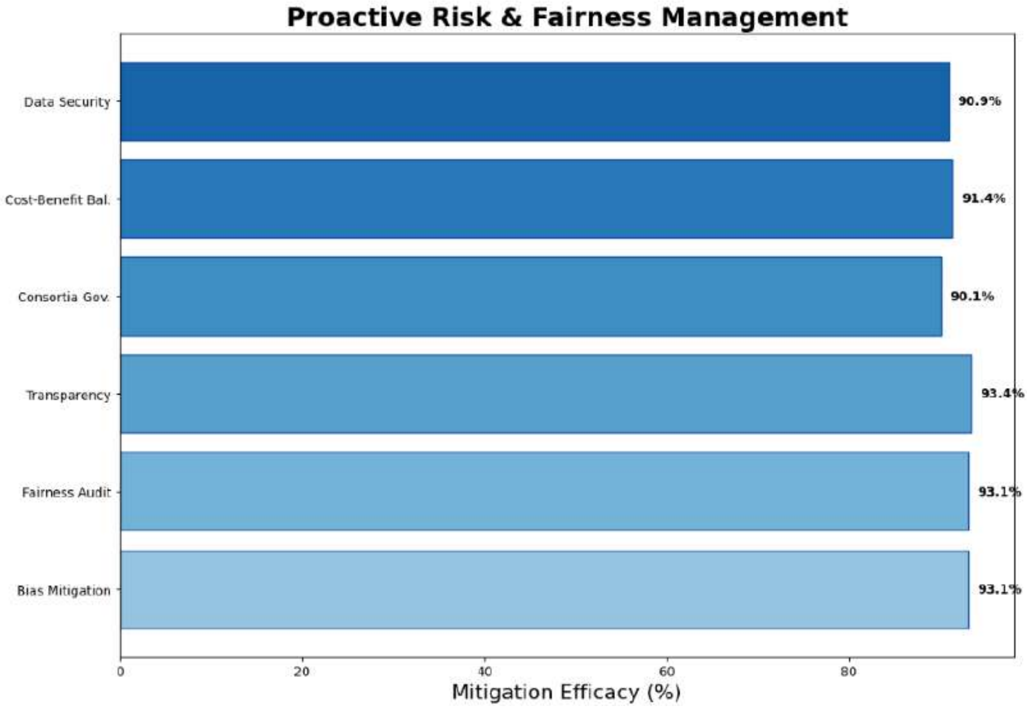

Fig 10.4: Proactive Risk & Fairness Management

10.7. Conclusion

The analysis of the key aspects of designing, deploying, and managing Autonomous Insurance Intelligence supports the evidence-based conclusion that, when these systems and solutions operated in the insurance sector are governed and audited in alignment with widely accepted laws and regulations, the issues of fairness, accountability, transparency, and reliability can be successfully mitigated. Accordingly, the development, launch, and day-to-day functioning of Autonomous Insurance Intelligence systems should neither be impeded by excessively restrictive frameworks nor enshrined without due consideration of the likely benefits and potential harms.

The investigation has nevertheless pointed to prominent gaps in knowledge that merit further research before Autonomous Insurance Intelligence can be confidently embraced or rejected by market players and consumers and jurisdictions worldwide. Special attention should be devoted to the establishment of robust AI, digital, and insurance regulations by properly mandated organisations, to a better understanding of market behaviour in the presence of Autonomous Insurance Intelligence systems so that competition, innovation, and consumers' welfare can be optimised, and to the definition of standards and best practices that ensure the safe and trustworthy development of Autonomous Insurance Intelligence, with proper attention to the underlying IT systems and services partial or fully swallowed by AI. Finally, it must be acknowledged that the underlying data and technological foundations of Autonomous Insurance Intelligence are currently not fully inclusive. As such, the analysis provides food for thought for public authorities and insurance regulation and supervision or conduct bodies seeking to foster the sustainable development of AI.

10.7.1. Summary of Key Insights and Future Directions

The preceding analysis of Autonomous Insurance Intelligence is intended to support discussion and stimulate research in a nascent field of inquiry that warrants greater examination, particularly from a legal and ethical perspective. The definition of Autonomous Insurance Intelligence implies that the relevant technologies are employed at least to some degree in an autonomous manner, i.e., with little or no human intervention. Such technologies are increasingly used in business, consumer, and other contexts that involve critical and potentially high-risk decisions, and therefore their use in insurance raises questions about their governance—and, in particular, their ethical implications. Three core ethical principles—fairness, transparency, and reliability—were identified, and their implications for insurance applications were discussed. Having established their relevance, the following pluralistic framework was proposed: criteria to determine whether a technology is autonomous were developed and five main sources of risk were identified.

The assessment also confirmed that technological advances in Autonomous Insurance Intelligence will probably lead to a reallocation of business profits, an intensification of competition, and the entry of new players. However, the benefits of more competitive markets will not necessarily flow to consumers in the form of lower prices. Moreover, there are some indications that these technologies will create new forms of economic exclusion, making consumers in some market segments worse off. Finally, recrimination tools are needed to protect society from potential harmful consequences of these technological advances, and especially from those that are unintended. These new forms of protection are likely to take the form of individualized recommendation systems that help consumers identify the offer that is least likely to cause them harm.

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