REDUCING INFORMATION ASYMMETRY IN AUTOMOTIVE INSURANCE THROUGH ADVANCED TECHNOLOGY STRATEGY: A STUDY OF EMERGING MARKETS

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Abstract

The information asymmetry, which is a critical challenge in the insurance market, primarily manifests as adverse selection, moral hazard, and fraud. This paper provides a conceptual clarification and categorization of these phenomena between the insurer and the insured. The study also revisits existing statistical modeling tools to formalize insurance fraud risk within a deterministic audit framework, drawing inspiration from the foundational work of Picard (1996, 2001) and Bond and Crocker (1997). The major contribution of this research lies in the modeling of the optimal insurance contract designed to incentivize policyholders to declare the actual amount of their loss under deterministic audit conditions. This formalization allows us to derive an optimal indemnity that maximizes utility while effectively controlling moral hazard. Furthermore, this research highlights numerous advanced techniques (including artificial intelligence [AI]) for overcoming these asymmetry problems. It provides concrete examples of the successful implementation of these strategies by insurance companies in specific emerging markets, such as Saudi Arabia and Tunisia. Finally, many avenues are proposed to find solutions to address the challenges of personal data collection and protection posed by the integration of AI in the insurance sector.

Keywords: Risk, Automobile Insurance, Adverse Selection, Moral Hazard, Advanced Technologies, AI, Emerging Countries

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1. INTRODUCTION

The issue of asymmetric information has emerged as one of the most influential theoretical concepts for understanding the dynamics of competitive insurance markets. Research demonstrates that this problem arises when crucial information is unequally distributed among agents. In this context, the relevant agency theory, developed by Jensen and Meckling (1976), focuses on the design of bilateral contracts aimed at resolving various coordination problems between a principal and an agent. By identifying the insurer as the principal and the insured as the agent, the agency theory effectively analyzes the relationships inherent in insurance contracts, particularly within automobile insurance. This information asymmetry typically gives rise to three distinct phenomena: moral hazard, adverse selection (or anti-selection), and fraud. As demonstrated by Ehrlich and Becker (1972) and Briys and de Varenne (2001) through self-protection or self-insurance activities, the insured can modify either the value of a loss during a disaster or the probability of their risks. While the issues arising from information asymmetry are well-documented in developed insurance markets, empirical studies in Tunisia addressing these complexities remain limited. Foundational works, such as Feki (2017) and Karaa (2018), have successfully identified moral hazard using historical data (e.g., 2008–2010 data). However, this work presents two significant shortcomings: first, it primarily focuses on the identification of the problems (adverse selection and moral hazard); second, it relies on older datasets and traditional methodologies rather than solution-based modeling. Similarly, while the rapidly evolving Saudi Arabian insurance market is undergoing a massive digital transformation driven by Vision 2030, academic literature has largely focused on market structure and growth, the specific econometric modeling of adverse selection and moral hazard in the motor insurance sector remaining scarce. Moreover, the existing literature lacks an integrated approach to modeling/formalizing the fraud issue that proposes cutting-edge technological solutions to manage both adverse selection and moral hazard. This paper is designed to fill these critical gaps; it offers a substantial and multi-faceted contribution to the existing literature on information asymmetry and insurance economics, with a specific focus on emerging markets like Tunisia and Saudi Arabia. Our novelty is established across three major pillars.

First, defining and formalizing moral hazard and fraud, especially within a deterministic audit framework. This modeling determines the optimal insurance contract that incentivizes the insured to declare the actual loss amount. This moves beyond only identification (the existing literature's focus or the descriptive analysis) toward a formal, prescriptive, solution-oriented modeling of fraud and optimal contract design. Second, the novelty culminates in an emphasis on numerous cutting-edge techniques designed to overcome the challenges of formalization in the preceding theoretical models. This includes identifying innovative solutions and services to bridge the information gap between the insurer and the insured (e.g., Internet of Things [IoT], telematics), thereby enhancing personalization of insurance services and optimizing risk management. Third, to anchor these solutions in reality, the study provides pertinent examples of adoption from various countries, particularly the emerging market landscapes of Tunisia and Saudi Arabia, illustrating how these technologies are actively being deployed to combat information asymmetry and fraud.

The remainder of this article is organized as follows. Section 2 reviews the relevant literature addressing asymmetric information, defining the three types of asymmetric information. Section 3 describes the methodology that consists of modeling fraud, seeks to identify the optimal insurance contract for the insured to declare the true loss amount in a context of deterministic audit, and the result derived. Section 4 highlights and proposes advanced technologies to address asymmetric information. Section 5 provides pertinent examples of artificial intelligence (AI) adoption, particularly from emerging markets. Finally, Section 6 of the paper proposes solutions to the challenge of personal data protection by AI insurance.

2. LITERATURE REVIEW

The new microeconomic theory has significantly contributed to the understanding of information asymmetry in the automotive insurance sector. This literature review highlights research focusing on three types of asymmetric information: moral hazard, adverse selection, and fraud. It also explores the emergence of advanced technologies in mitigating these challenges.

2.1. Moral hazard

Pioneering work by Arrow (1963), Pauly (1968), and Zeckhauser (1970) laid the groundwork for understanding moral hazard in the insurance market. In Tunisia, studies specifically addressing moral hazard in car insurance are limited. However, some research, like Ghali (2002), has analyzed the Tunisian car insurance pricing system using optimal pricing models to incentivize carefulness. Karaa and Benlagha (2015) investigated asymmetric information among new drivers in the Tunisian automobile insurance market using a bivariate probit model, finding strong evidence for its presence in this group.

Also, Karaa (2018) empirically studied the existence of asymmetric information and specifically provides evidence of moral hazard and distinguishes it from adverse selection in the Tunisian car insurance sector using longitudinal data from a major insurance company.

2.1.1. Definition of moral hazard

Moral hazard can be defined as any deviation from a correct human behavior that may cause trouble for the insurer when there is a risk. More precisely, when the risk is significantly influenced by the insured's behavior, which is not directly monitored by the insurer (Ellouze, 1995). Unlike adverse selection, moral hazard is a risk that arises after the conclusion of a contract.

Consequently, some less vigilant driver might exploit legal loopholes stemming from this informational asymmetry to their advantage. Arrow's (1963) study identified two primary forms of moral hazard: negligence and intentionally sinister acts. Later, Dionne and St-Michel (1991) maintained a similar definition but expanded upon the types of incentive changes that could alter the probability calculations an insurer relies upon. These include two types of moral hazard:

- The incentive to not undertake the optimal level of prevention (*ex-ante* moral hazard): This occurs before a loss.
- The incentive to exaggerate the amount of a claim after an accident (*ex-post* moral hazard): This occurs after a loss.

2.1.2. Types of moral hazard

Ex-ante moral hazard

The work of Holmström (1979) and Shavell (1979) significantly advanced research into *ex-ante* moral hazard. Insurance theory posits that individuals benefiting from an insurance contract are less incentivized to adopt preventive behaviors, thereby increasing their exposure to risk. Shavell (1979) argued that an optimal insurance contract must incorporate mechanisms that encourage insured parties to engage in preventive actions, such as self-insurance and self-protection. Ehrlich and Becker (1972) were pioneers in this field, demonstrating that risk management can involve three instruments: market insurance, self-insurance, and self-protection.

Ex-post moral hazard

In the context of automobile insurance, this risk materializes when the insured can take actions that affect the distribution of their losses after an accident has occurred. Insurance can thus induce the insured's behavioral changes, leading to an increase in the number of falsified compensation claims or a rise in claimed amounts, which, in turn, generates substantial costs for the insurer (Cummins & Tennyson, 1996). According to Dionne and St-Michel (1991), *ex-post* moral hazard is similar to an attempted fraud.

2.2. Adverse selection

The concept of adverse selection was initiated by Arrow (1963) and Rothschild and Stiglitz (1976). Subsequent contributions from researchers like Ellouze (1985), Stewart (1994), Chassagnon and Chiappori (1997), de Meza and Webb (2001), and Jullien and Salanié (2000) have further developed this area.

2.2.1. Definition of the adverse selection

As Ellouze (1995) defines it, adverse selection arises from the insurer's inability to identify certain characteristics of the insured that are essential for accurate premium determination. It occurs when the insured possesses superior knowledge regarding the risk's indicators and parameters compared to the insurer.

This phenomenon can be analyzed from two perspectives: either individuals differ in their prevention costs or the probability of a disaster's occurrence, or they vary in their risk aversion (Stewart, 1994; Chassagnon & Chiappori, 1997; de Meza & Webb, 2001; Jullien & Salanié, 2000). In such situations, insurers are unable to distinguish between "low-risk" and "high-risk" clients, and consequently, they cannot tailor insurance pricing to individual risk profiles. The lack of information leads to uniform pricing for all heterogeneous individuals (Pannequin, 2011). Chassagnon (1996) offered another perspective, describing adverse selection as a scenario where an insurer covers a large number of heterogeneous agents who have a probability of assuming damage. It offers a single price which reflects the average loss of probability for the representative agent of this economy. This creates a selection phenomenon based on prices, which is deemed "adverse" because it is the high-risk individuals who remain insured. Essentially, low-risk individuals end up subsidizing high-risk individuals. This disparity is unacceptable to low-risk insureds, potentially discouraging them from purchasing insurance. Conversely, high-risk individuals are drawn to the seemingly low premiums, encouraging them to buy an insurance contract and maintain their risky behavior. This dynamic skews the insurer's portfolio with a disproportionate number of high-risk clients, destabilizing the insurance market. As Rothschild and Stiglitz (1976) observed, such a situation tends to drive away good risks, making insurance excessively costly for those less likely to incur losses.

2.2.2. Consequences of adverse selection on the insurance market

Adverse selection poses a significant threat to the stability and efficiency of insurance markets. In Tunisia, this phenomenon is a primary driver of financial deficits within the sector, largely due to two key factors. Firstly, the mandatory nature of certain insurance policies, such as the civil liability and appeal to third parties' fires contract (Ellouze, 1995), means insurers lack the opportunity to segment clients based on their contract choices. This forces a uniform pricing structure, where both "good" and "bad" risks pay the same premium.

Secondly, the compulsory nature of car insurance leads many drivers to view it merely as a tax, prompting them to subscribe only to the bare minimum coverage. The application of a single insurance price, as seen in Tunisia's historical context (e.g., since 1971), is far from optimal because pricing isn't personalized. So, an insurer might charge the same premium for a highly experienced driver with 30 years on the road as for a novice who just obtained their license. Unfortunately, premiums often fail to account for crucial risk factors such as age, gender, years of driving experience, or past incidents like license withdrawals, accident history, or alcohol-related offenses.

2.3. Insurance fraud detection

Insurance fraud modeling has garnered significant attention from theorists over the years, as evidenced by works from Derrig and Ostasewski (1995), Picard (1996), Brockett et al. (2002), Belhadji and Dionne (1999), Viaene and Dedene (2004), and Weisberg and Derrig (1991). Econometric models, such as simple regression and probit logit models, emerged in the 1990s to study insurance fraud (Weisberg & Derrig, 1998; Brockett et al., 1998; Artís et al., 1999; Belhadji et al., 2000).

Fundamentally, fraud in the insurance context is an asymmetric information problem between the contracting parties. Doctrinally, it occurs when an insured commits a voluntary act to illegitimately benefit from compensation to which they are not entitled. Viaene and Dedene (2004) further clarified that fraud constitutes a legal transgression requiring a false material declaration made with the purpose of deceiving the insurer and securing an illicit profit or compensation.

In essence, while an insured faces a loss event, they might subsequently decide to commit fraud by reporting a fabricated incident or inflating the extent of the damage. Picard (1996) and Borgi (2006) identified two main types of fraud: opportunistic fraud, which involves taking advantage of an existing accident for personal gain, and planned fraud, which stems from a deliberate criminal act. Expanding on this, Weisberg and Derrig (1991) and Hoyt (1989) distinguished four fraud categories: planned fraud, exaggeration of damage, false reporting of facts, and false statements of risk.

2.4. Advanced technologies and asymmetric information

The application of advanced technologies, particularly AI, in the insurance market to address asymmetric information is a growing area of research.

2.4.1. Telematics data

Geyer et al. (2020) demonstrated how telematics data can mitigate asymmetric information by revealing private driving characteristics. Their research highlighted the potential for creating more accurate insurance profiles based on driving factors like distance driven, number of rides, and speeding, even accounting for endogeneity of the driving factor using local weather conditions.

On the other hand, Usman et al. (2024) leveraged telematics data on driving behavior variables to assess driver risk and predict future insurance claims in a case study using a representative telematics sample. They categorize drivers according to their driving habits and establish premiums that accurately reflect their driving risk.

On the other side, Malik et al (2022) emphasized that telematics is a necessity in the Indian market, as it can assist companies in reducing the problems of both adverse selection and moral hazard; enable precise ascertainment of insurance premiums based on behavioral factors such as driving habits, and distance travelled by the policyholders.

Moreover, Cevolini and Esposito (2022) discussed how telematics reverses information asymmetry by giving the insurer a behavioral score to determine the price of the policy. Highly relevant for any market adopting insurance technology.

Finally, we can also add the research of Yang et al. (2025), who empirically investigated the impact of digitalization on mitigating a specific type of adverse selection known as "cream skimming" within China's property and casualty (P&C) insurance sector.

2.4.2. Data-driven solutions and artificial intelligence

Pernagallo (2024) discussed how AI-based, data-driven solutions can address both old and new problems of information asymmetry, offering advantages over traditional approaches. Authors like Bartholic et al. (2021) highlight the potential of smart contracts and blockchain technology to prevent misuse, mishandling, or over-collection of user data by insurers.

2.4.3. AI and machine learning for fraud detection

Benedek et al. (2022) surveyed the automobile insurance fraud detection literature from 1990 to 2021, emphasizing the transformation from traditional statistics-based methods to data mining and AI-based approaches. Their study pointed out the benefits of these new methods, while also identifying deficiencies such as the lack of cost-sensitive approaches and reliable datasets.

2.4.4. Usage-based insurance

Arvidsson (2010) explored the potential of usage-based insurance (UBI), also known as pay-as-you-drive (PAYD), pay-how-you-drive (PHYD), or pay-as-you-go (PAYG). Her research showed that UBI enables full coverage at an actuarially fair premium for both low- and high-risk drivers and incentivizes them to adopt safer behaviors, thereby reducing risk-taking.

3. RESEARCH METHODOLOGY

3.1. Modeling fraud in a context of deterministic audit

This fraud model is inspired by the work of Picard (1996, 2001) and Bond and Crocker (1997), which addresses it in the presence of deterministic auditing.

The model involves two agents: 1) a risk-neutral insurance company and 2) a risk-averse insured agent. The agent's preferences are represented by:

- U — a utility function, of the Von-Neumann-Morgenstern type; this function is strictly increasing ($U' > 0$), twice continuously differentiable, and strictly concave ($U'' < 0$);
- W — the initial wealth of the insured or W_0;
- X — the risk of insurable loss or the loss amount;
- P — the insurance premium paid by the insured.

The model assumes that X can take two possible random values, L or M, with $L < M$.

Nature defines two possible states:

$$\begin{cases} \text{loss with a probability: } \pi \\ \text{No loss with a probability } (1-\pi) \end{cases} \tag{1}$$

Let's assume that the amount of the loss can only take two possible random values:

$$\begin{cases} M \text{ with a probability of } \dfrac{q_1}{\pi} \\ L \text{ with a probability of } \dfrac{q_2}{\pi} \end{cases} \tag{2}$$

Remember that the reserve utility is funds set aside by the insurance company, including liabilities for unearned premiums and the estimated costs of unpaid claims.

Thus, the reserve utility of the insured is written as follows:

$$U = \pi\left(\frac{q_1}{\pi}\,U(W-M) + \frac{q_2}{\pi}\,U(W-L) + (1-\pi)U(W)\right) \quad (3)$$

where,

- L — the threshold of the loss (or "claim");

Let's consider that the realization and the magnitude of the loss represent private information held by the insured and can be verified by the insurer.

The insured, having suffered from a loss X, can decide to defraud and declare risks of probable loss L or M to their insurer. The latter will carry out a verification based on a loss threshold L. The verification region R is defined by [L, M], representing the range of losses where the insurer conducts an audit to ensure transparency. The model deals with an insurer who must audit a claim to verify the actual loss (because the insured might lie about the damage), the verification region R is a critical decision variable. The insurer doesn't audit every claim (it's too expensive). The region R = [L, M] tells the reader exactly when the insurer will trigger an audit (e.g., only for losses between a certain threshold).

In what follows, we will present the structure of the model:

1. For the first state of nature: When the insured suffers from damage or loss X, they are faced with two risks of probable losses, M and L.

$$\begin{cases} X = M \\ X = L \end{cases} \quad (4)$$

Table 1. If the insured suffers from a loss with a probability π

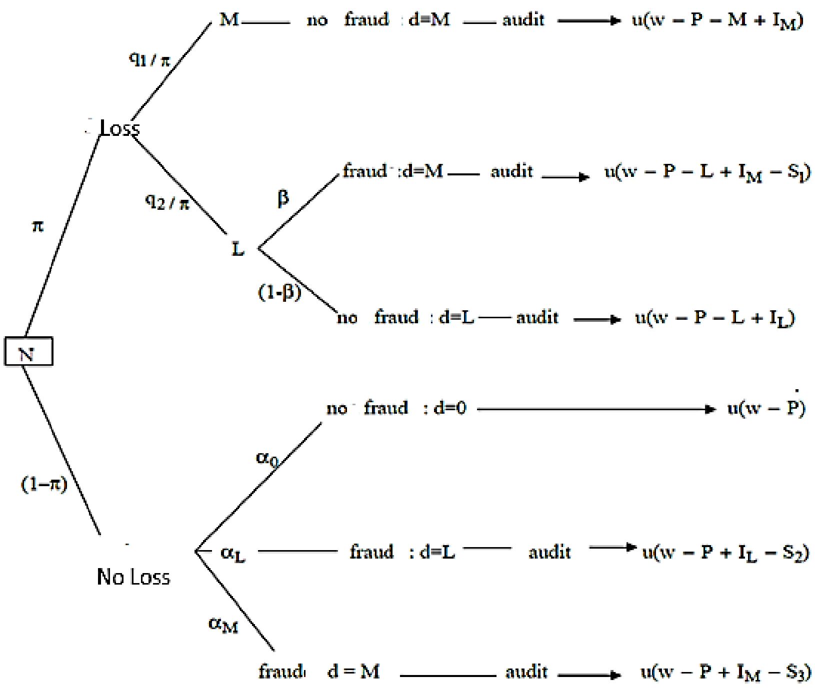
If the insured suffers from a loss or damage X of an amount M, then X = M	***If the insured suffers from a loss or damage X of an amount L, then X = L***
Their optimal strategy is then to tell the truth: $d = M$. Their declaration will be verified by their insurer. If they are honest, they will receive the insurance reimbursement (I_M). They will have the following utility function: $U(W-P-M+I_M)$	If their strategy is defined by the probability β of committing fraud by declaring $d = M > L$. In this case, the insured's utility is written as: $U(W-P-L+I_M-S_1)$ (In the case of fraud, the fraudulent declaration is followed by a sanction). And the probability $(1-\beta)$ of not committing fraud and declaring $d = L$. In this case, the insured's utility is written as: $U(W-P-L+I_L)$, if they are honest.

2. For the second state of nature, when the insured does not suffer from damage (non-loss), their strategy is characterized by the following two fraud possibilities. We schematize this model in Figure 1.

Table 2. If the insured suffers from no loss with a probability $(1-\pi)$

Declare d = L with a probability α_L	***Declare d = M with a probability α_M***
In this case, the insured will be sanctioned by S_2 after detecting the fraud. They will, therefore, have the following utility function: $U(W-P+I_L-S_2)$	They will be sanctioned by S_3. This eventuality gives them a utility equal to: $U(W-P+I_M-S_3)$, such that $\alpha_{M+}\alpha_L+\alpha_0 = 1$, where α_0 represents the probability of saying the truth.

Figure 1. Fraud strategies in the event of a deterministic audit



3.2. The optimal insurance contract for the insured in case of a deterministic audit

The optimal insurance contract is designed to incentivize the insured to declare the true amount of their loss. To eliminate any fraudulent behavior (i.e., achieve zero probabilities of fraud), the utility gained from being truthful must be strictly greater than any utility derived from fraud, especially when considering potential sanctions. In other words: U (fraudulent declaration + sanction) < U (honest declaration).

This crucial principle defines the incentive constraints as follows:

$$U(W - P - L + I_M - S_1) < U(W - P - L + I_L) \quad (5)$$

$$U(W - P + I_L - S_2) < U(W - P) \quad (6)$$

$$U(W - P + I_M - S_3) < U(W - P) \quad (7)$$

A contract is considered a disclosure contract if it is compatible with these incentive constraints. This means:

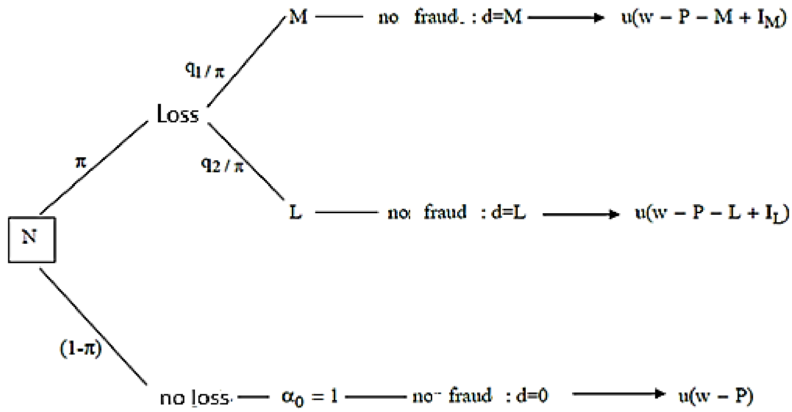
$$\begin{cases} S_1 > I_M - I_L \\ S_2 > I_L \\ S_3 > I_M \end{cases} \quad (8)$$

This allows us to say that refusing to reimburse the damage is not enough to encourage the insured to be honest. Indeed, refuting any fraudulent behavior leads to having zero probability of fraud. In other words, it is necessary that:

$$\begin{cases} \beta = 0 \\ \alpha_M = 0 \\ \alpha_L = 0 \end{cases} \quad (9)$$

By integrating this constraint into the decision tree, we would show how the insurer's design of premiums, reimbursements, and sanctions influences the insured's optimal choice to either be honest or commit fraud. This design is manifested in Figure 2.

Figure 2. Fraud strategies when integrating these constraints (at the equilibrium in the case of non-fraud)



Thus, the expected utility function for the insured can be formulated as follows:

$$EU = \pi \times \left({}^{q_1}/_{\pi}\right) \times U(W - P - M + I_M^*) + \pi \times \left({}^{q_2}/_{\pi}\right) \times U(W - P - L + I_L^*) + (1 - \pi) \times U(W - P) \quad (10)$$

The optimal insurance contract consists of determining: I_L^*, I_M^*, and P^*. The profit constraint for the insurer is typically expressed as the expected profit being greater than or equal to zero to ensure that it does not operates in a loss. It can be summarized as:

$$P - \pi \times \left({}^{q_1}/_{\pi}\right) I_M - \pi \times \left({}^{q_2}/_{\pi}\right) I_L - [\pi + (1 - \pi) \times (\alpha_L + \alpha_M)] \times c \geq 0 \quad (11)$$

where,

- P — premium received by the insurer or the premium income;
- π — probability of a loss event and $1 - \pi$ is the probability of no loss;
- q_1, q_2 — probabilities of specific loss types (M and L) conditional on a general loss event;
- ${}^{q_1}/_{\pi} = p_M$ is the part of the loss M and ${}^{q_2}/_{\pi} = p_L$ is the part of the loss L;
- I_M, I_L — indemnity payouts for losses M and L;
- c — the exogenous cost of the audit, which evaluates a company's cost structure to ensure financial transparency and management;
- α_L, α_M — probabilities of auditing different loss types, L and M, respectively;
- $[\pi + (1 - \pi) \times (\alpha_L + \alpha_M)] \times c$ — this term represents the expected costs of verification/auditing or other administration expenses for the insurer, considering the probabilities of different states and associated audit decisions.

In essence, this constraint states:

$$Expected\ premium\ revenue - Expected\ payouts - \frac{Expected\ administrative}{Verification\ costs} \geq 0 \quad (12)$$

This is a critical constraint for the insurer to be willing to offer the contract. It's common in optimal contract problems to have both types of constraints:

Participation constraint (PC) for the agent — it is also known as the individual rationality (IR) constraint — is the mathematical requirement that the expected utility from accepting the insurance contract must be greater than or equal to the expected utility of not accepting the contract (the reservation utility).

The general form of the PC is:

$$PC = E[U(W_{Wealth\ with\ insurance\ contract})] \geq E[U(W_{Wealth\ with\ insurance\ contract})] \quad (13)$$

where, $E[U(W_{Wealth\ with\ insurance\ contract})]$ is the expected utility if the insured accepts the insurance contract. It is a weighted average of the utility the insured derives from their final wealth in each possible state (loss with indemnity, loss with no indemnity due to audit, no loss, etc.), after considering the premium, any payouts, and the outcomes of audits.

$$E[U(W_{Wealth\ with\ insurance\ contract}] = p_M \times U(W_0 - P - M + I_M^*) + p_L \times U(W_0 - P - L + I_L^*) + (1 - p_M - p_L) \times U(W_0 - P) \quad (14)$$

It considers:

- their initial wealth (W_0);
- the premium (P) they pay;
- the potential losses (M and L) ;
- the indemnities (I_M^* and I_L^*) they receive for each loss type;
- the probabilities of these loss events (e.g., p_M for loss M, and p_L for loss L).

There are two possible cases of the expected utility with insurance:

- If loss occurs (with probabilities p_M and p_L): Final wealth is $W_0 - P + I_M^*, I_L^*$.
- If no loss occurs (with probability $1 - p_M - p_L$): Final wealth is $W_0 - P$.

However, the right side of Eq. (13) — $E[U(W_{Wealth\ with\ insurance\ contract})]$ or $U_{Insured\ reserve}$ is the reserve or reservation utility that is the expected utility if the insured rejects the insurance contract. In this case, they keep their initial wealth but bear the full burden of any losses.

$$U_{Insured\ reserve} = p_M \times U(W_0 - M) + p_L \times U(W_0 - L) + (1 - p_M - p_L) \times U(W_0) \quad (15)$$

There are two cases of the reservation utility:

- If loss occurs (with probabilities p_M and p_L): final wealth is W_0 minus the loss suffered (L or M).
- If no loss occurs ($1 - p_M - p_L$): final wealth is W_0.

Therefore, when replacing both sides — Eqs. (14) and (15) — the PC for the insured will be:

$$PC = p_M \times U(W_0 - P - M + I_M^*) + p_L \times U(W_0 - P - L + I_L^*) + (1 - p_M - p_L) \times U(W_0 - P) \geq p_M \times U(W_0 - M) + p_L \times U(W_0 - L) + (1 - p_M - p_L) \times U(W_0) \quad (16)$$

While traditional deterministic audit models often rely on specific, predefined rules and thresholds (like fixed ratio analysis), the newest and most effective alternative to deterministic audit modeling for fraud detection is the integration of machine learning (ML) algorithms like gradient boosting and neural networks, often complemented by big data analytical techniques like process mining and Benford's Law.

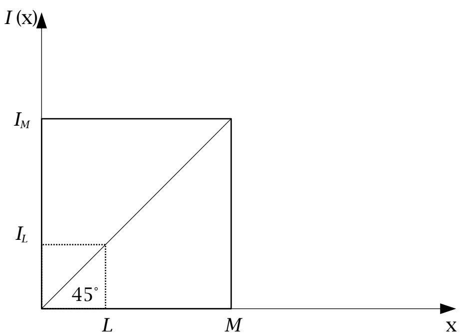
4. RESULTS

The resolution of this program (PC) allows us to draw the following conclusions:

- An optimal insurance contract with deterministic audit satisfies the following conditions: $I_M > I_L$ for $M > L$.
- The insurance indemnity is an increasing function of the damage: $I_x = 0$ for $x < L$.
- The compensation is zero for any damage less than L: $I_M = M$ and $I_L = L$.

The complete insurance is optimal beyond the expertise threshold (see Figure 3).

Figure 3. The optimal insurance compensation



The key finding across various models, such as the one of Picard (2001) and Bond and Crocker (1997), is that the optimal contract under deterministic auditing is typically a pure deductible contract which provides 100% coverage above a fixed deductible amount, after the insurer verifies private information presented by the insured at a verification cost. This design discourages policyholders from inflating small claims because they are fully responsible for the initial loss to a certain threshold (the deductible), and any attempt at minor fraud would be immediately detected for larger claims that cross the audit threshold.

After having an idea about an optimal insurance contract with deterministic audit, the last part of this paper exhibits the innovation of the advanced technologies to deal with asymmetric information matters.

5. DISCUSSION

The core issue of asymmetric information between the insured and the insurer in automobile insurance leads to inefficiencies and increased costs. However, advancements in big data, AI, and the IoT offer innovative solutions to address this problem.

5.1. The role of connected objects (IoT and AI) for driver risk evaluation

The rise of insurance technology (Redsen Consulting, 2026) and the proliferation of connected objects have revolutionized how insurers assess the risk of the driver. Traditional insurance mechanisms rely on statistical probabilities of risk occurrence. Now, with data points such as speed, sudden braking, adherence to limitations, mileage, and frequency of use collected from vehicle telematics or connected devices, a more precise probability of risk occurrence can be determined. AI's ability to quickly analyze these massive datasets provides insurers with reliable, real-time insights into insured behavior. A prime example is AXA France's AXA Secure GPT, an internal AI platform developed in partnership with Microsoft. It allows for customer offers to be adjusted based on their history or risk profile and optimizes risk management by identifying potential claims or proposing preventive actions, particularly for climate-related damages (natural disaster, fire, flood). While the widespread adoption of telematics in vehicles is growing, challenges remain, as not all drivers have compatible vehicles or are ready to embrace such systems. This necessitates hybrid solutions. Beyond integrated telematics, other devices like dashcams are gaining traction, not just for dispute resolution in accidents but also for advanced features like automatically alerting emergency services with GPS coordinates and even driver medical data in the event of non-response after an accident. Furthermore, sensors like the Xee box or Samsung Connect Auto monitor vehicle health, alerting drivers to potential failures and maintenance needs. Startups like OoCa have emerged to analyze the demand for driver data collection and behavior analysis. Their connected boxes, easily linked to a vehicle's on-board diagnostic (OBD) socket, collect and transmit driving data via Bluetooth to mobile applications, providing drivers with immediate feedback on their driving quality and potential benefits for good behavior. The European Union is enhancing vehicle safety and data collection with new regulations. By 2024, all vehicles in Europe will be mandated to include a vehicle data recorder, often referred to as a "black box". This device, governed by Regulation (EU) 2019/2144 (European Union, 2019), records crucial information such as speed, acceleration, braking, seat belt usage, and collision force. It specifically stores data from the moments surrounding an accident (30 seconds before and 10 seconds after impact). While primarily accessible to investigators, judicial authorities, and research institutes (Munschi, 2022) and not typically insurers, this initiative is part of a broader trend. Beyond these mandated recorders, the IoT (Perrin, 2021) is set to revolutionize insurance processes by automating tasks like incident reporting, promising more efficient claims management.

5.2. AI-driven personalization of insurance contracts and premiums

Artificial intelligence plays a crucial role in enabling the personalization of insurance products. Studies, such as one by Accenture (2021), reveal that 88% of French consumers desire more personalized insurance offers, reinforce this need. The primary objective in this personalization trend is the modularity of offers, leading to usage-based pricing. This includes: PAYD, PHYD, or PAYG.

- PAYD contracts: Premiums are calculated based on the number of kilometers traveled, appealing to infrequent drivers.
- PHYD contracts: Tariffs evolve according to the driver's actual behavior, rewarding good drivers with potential premium reimbursements for responsible road conduct. This model can even allow well-behaved policyholders to recover a portion of their paid premiums, effectively incentivizing adherence to traffic laws and promoting accident prevention. Insurance technologies like Extra Drive and Metromile are pioneers in this space (Redsen Consulting, 2026).
- PAYG contracts: Offered by startups like WILOV (Perrin, 2021), this model calculates premiums based on the number of days driven, providing flexibility for occasional users. Such dynamic adjustments of insurance premiums, reflecting current risk profiles rather than static estimates, significantly reduce information asymmetry between insurer and insured. Companies like Allianz (connected driving) and Direct Assurance (you drive) utilize connected boxes (telematics boxes) to assess their insureds' driving behavior. A notable success story is Root Insurance in the United States, which saw an 827% increase in contracts in the first half of 2019 compared to 2018. Root Insurance achieves competitive pricing by selecting only the best drivers, requiring a two-three week driving test via their mobile application to assess the driving behavior. The recorded driving data from this test forms the basis for the insurance quote, with 35% of the premium directly determined by driving behavior. Similarly, the alliance of Olivier Assurance Auto, Norauto, and Next base offers insured individuals a 10% saving on their insurance premium, further demonstrating the financial incentives for responsible driving (Plasse, 2021).

5.3. Enhanced customer relations with chatbots and virtual assistants

To improve customer service, insurers are increasingly adopting AI-powered chatbots and virtual assistants to analyze customer data and offer tailored products to their needs. For instance, AXA utilizes chatbots to provide 24/7 personalized assistance, while innovative startups like Choov are developing tools to empower insurance distributors with better customer advisory capabilities. The adoption of AI-driven chatbots can significantly reduce insurers' operational costs by up to 30%, according to Erk et al. (2020). A prime example is MAIF, which has successfully deployed a chatbot capable of handling customer requests autonomously, automating repetitive tasks like information requests and basic claims processing. Another AI chatbot application is Hayat, developed by Macir Vie in Algeria, which offers personalized advice to customers.

5.4. AI's role in combatting insurance fraud

Fraud poses a significant and costly financial challenge for insurance companies. In 2022 alone, insurance fraud in France reached a staggering 587 million euros, underscoring the urgent need for advanced technologies to curb these losses (Nolf, 2026). The forms of fraud are diverse, ranging from invented claims and exaggerated damages to false invoices. To tackle this pervasive issue, AI-driven data analysis helps insurers to detect, prevent, and predict such forms of fraudulent and suspicious behavioral activities, enabling proactive risk management and significantly reducing potential fraud. For instance, Covéa (MAAF (*Mutuelle d'Assurance des Artisans de France*) — Insurance Mutual for the Craftsmen of France, MMA (*Mutuelles du Mans Assurances*) — Le Mans Mutual Insurance, GMF (*Garantie Mutuelle des Fonctionnaires*) — Mutual Guarantee for Civil Servants, etc.) utilizes predictive analysis for this purpose, substantially reducing fraud-related costs.

5.5. AI for loss prediction and natural risk management in insurance

The increasing frequency and intensity of natural disasters underscore the importance of proactive risk management. The landscape of insurance is rapidly evolving, with over half of claims-related activities projected to be automated by 2030 (Balasubramanian et al., 2021). A key driver of this transformation is generative AI (GAI), which is being used to predict such catastrophic events, often referred to as "sinisters" in the insurance industry. AI achieves this by analyzing vast amounts of climate and environmental data. It then simulates various scenarios to create highly accurate predictive models. For instance, Generali France has successfully implemented such models to anticipate natural disasters like floods and storms, allowing insurers to anticipate, model, and respond effectively to these kinds of losses.

5.6. Automation of repetitive tasks through the AI and robotic process automation revolution

The insurance sector is undergoing a significant transformation in France, with a continuous rise in the automation of administrative and repetitive tasks (Balasubramanian et al., 2021). At the heart of this transformation lies AI and robotic process automation (RPA). They excel at processing massive volumes of data in real-time, dramatically improving efficiency, speed, and accuracy across various operations. Tasks that traditionally demanded intensive manual processing — such as managing information requests, handling claims, or underwriting contracts — are now largely automated. In essence, AI and RPA aren't just about reducing operational cost for companies; they're about optimizing human potential within the insurance industry to reallocate valuable human resources to activities that generate higher value.

5.7. AI's role in optimizing insurance business processes

Artificial intelligence algorithms are revolutionizing insurance operations, from claims management to underwriting new policies. By leveraging advanced techniques like ML and predictive analytics, these algorithms enable insurers to process vast amounts of data with remarkable speed and precision.

Consider the process of subscribing to a new home insurance policy: an algorithm can analyze customer data to proactively offer complementary products, such as car insurance, supplementary coverage, or valuable item protection. This personalized AI recommendation not only boosts conversion rates but also significantly enhances customer satisfaction and loyalty. For example, Zelros, a French startup, provides an AI solution that helps insurers manage their contract portfolios more effectively. By analyzing customer data, their AI identifies cross-selling and upselling opportunities, empowering insurers to increase sales while simultaneously strengthening customer retention. Beyond sales, AI is also streamlining administrative tasks. Similarly, the French neo-insurance company Alan exemplifies this by automating the processing of reimbursement requests. Thanks to their system, 98% of Alan's corporate clients spend less than two hours annually managing their health insurance. This efficiency is achieved by combining optical character recognition with natural language processing algorithms to extract information from invoices and medical documents, check coverage, and accurately calculate reimbursement amounts. After understanding the AI's role and benefits in the motor insurance market, it is important now to focus on concrete examples from emerging markets such as Tunisia and Saudi Arabia.

5.8. Examples of emerging markets applying AI in the motor insurance market

The adoption of advanced technologies is rapidly transforming the insurance landscape in various emerging countries, reducing the information gap between insurers and policyholders.

5.8.1. Saudi Arabia

In Saudi Arabia, the vehicle insurance sector is increasingly leveraging technology. A notable initiative comes from Najm for Insurance Services Company, which, in collaboration with the General Directorate of Traffic, launched a system for remote assessment of automobile accidents. This innovation significantly streamlines and accelerates the settlement process for the insured ("Remote motor claims", 2022). The Kingdom's broader commitment to AI is clear: Saudi Arabia established the Saudi Data and AI Authority as part of its Vision 2030, targeting a massive $20 billion investment in AI by 2030. According to Norton Rose Fulbright, the AI market in the Middle East is projected to generate up to $320 billion in added value by 2030, a financial potential that's driving rapid AI adoption across governments and businesses. Within Saudi Arabia's insurance space, AI has already delivered substantial efficiency gains, with over 50% of customer interactions in the sector managed by AI solutions by 2023 ("Insurance in the Middle East", 2024). Furthermore, companies like Abdul Latif Jameel are exploring expanding their telematics services. They're developing comprehensive platforms that include connected navigation systems and fleet management solutions to improve vehicle safety and efficiency. These platforms also provide invaluable data for insurers[1], enabling more accurate risk assessment and personalized offerings.

5.8.2. Tunisia

Tunisian insurers are also embracing AI to enhance customer experience and combat fraud. GAT

[1] https://alj.com/fr/transportation/expanded-vehicle-services

ASSURANCES, known for its innovation, recently launched an AI-powered tire diagnostics feature through its MyGAT mobile app (“Une première en Tunisie: GAT Assurances”, 2024). Car insurance customers can now get a free, accurate assessment of their tires’ condition simply by taking photos via the app.

The AI algorithm analyzes tire wear against safety standards, providing a comprehensive report with personalized recommendations. The MyGAT app is evolving into a full-fledged personal assistant, offering everything from policy management and claims tracking to online payments. In a move to foster local innovation, CARTE Assurances integrated AI in July 2020 to optimize auto claims management (“Une première en Tunisie, CARTE Assurances”, 2020). They partnered with the Tunisian startup DigiConstat to use its “Digi Fraud” solution. This system detects fraud attempts related to auto insurers by analyzing declarations for anomalies. Given the fairly high volume of suspicious files in the Tunisian insurance market, this automation aims to accelerate file processing and improve service quality for policyholders.

While offering numerous benefits, the AI integration brings to the forefront a significant challenge: the collection and protection of personal data.

5.9. Dealing with the challenge of personal data protection by AI insurance

This issue remains a major concern for policyholders, even as studies, like one by Harris Interactive in February 2019, suggest that over 70% of French individuals would be willing to share their personal data about their health, physical activity, or driving habits for reduced premiums. This willingness is further underscored by legislative moves, such as France’s draft mobility orientation law, which recently confirmed insurers’ authorized access to connected vehicle data.

This dynamic creates an urgent need for robust regulatory compliance with existing laws like Europe’s General Data Protection Regulation (GDPR), along with stringent regulations in jurisdictions such as Saudi Arabia and the United Arab Emirates, often requiring regular audits[2] and compliance assessments. Insurers also face the practical hurdles and costs of modernizing infrastructure — investing in necessary servers, databases, management software — and training employees to effectively integrate AI systems. Some experts propose innovative solutions to this data dilemma. In this context, Bartholic et al. (2021) argue that blockchain itself acts as a trusted agent for both insurers and the insured. Their proposed “Smart Auto Insurance” system, for instance, aims to minimize data sharing and control the release of sensitive data, thereby preserving data privacy and streamlining fault negotiation. It also serves as a global, low-resource record for risk rating rules. Furthermore, they demonstrate through game theory that clients using such a system are disincentivized from adversarial behavior, fostering a more trustworthy environment. Ultimately, balancing the immense potential of AI in insurance with the paramount need for data privacy and security is crucial. It’s about building systems that are not only efficient but also deserving of consumer trust.

[2] Insurance companies must conduct regular audits with compliance assessments to ensure that AI systems comply with standards.

6. CONCLUSION

This research successfully synthesized the multifaceted challenges posed by asymmetric information in the insurance sector and provided a dual-pronged approach for mitigation: theoretical modeling and technological integration.

This study effectively modeled fraud mitigation in the context of deterministic auditing, building upon the foundational works of Picard (1996, 2001) and Bond and Crocker (1997). Crucially, this paper contributes an optimal insurance contract design tailored to incentivize the insured to declare the actual loss amount under a deterministic audit regime.

The key finding across this modelling is that the optimal contract under deterministic auditing is typically a pure deductible contract, which provides 100% coverage above a fixed deductible amount.

On the other hand, this work extensively explored the huge role of AI, showcasing its potential in fraud detection, risk management, prediction, and evaluation, thanks to the connected objects, personalizing premium and contracts, enhancing customer relationships with chatbots, loss prediction, and optimizing insurance business process particularly within emerging markets like Saudi Arabia. However, this research preempts the significant ethical and practical challenges associated with AI — namely, data confidentiality and privacy and proposed smart contracts and blockchain technology as robust solutions to prevent the misuse, mishandling, or over-collection of user data by insurers.

While the core principles of optimal contracting (risk sharing, minimizing auditing costs, and addressing moral hazard/adverse selection) remain universal, the optimality of a pure deductible contract is complex and conditional and may be affected by several factors unique to emerging markets such as Sharia compliance, the general level of audit cost/effectiveness, and the need to promote consumer trust and insurance literacy. These constraints may necessitate a modified structure, such as a deductible combined with a coinsurance (sharing a percentage of the loss above the deductible) clause.

Moreover, while the presence of asymmetric information in the Tunisian automobile insurance market is recognized in the existing literature, there is limited work that empirically isolates the impact of moral hazard using recent data and advanced methodologies like ML (Feki, 2017; Karaa, 2018).

Future research can focus on these limits or extend the analysis to specific recovery tools, such as multi-periodic contracts, or evaluate the effectiveness of the bonus/malus thresholds and deductible flexibility in markets like Tunisia and Saudi Arabia to provide a practical outlook on the evolving landscape of insurance in the age of AI, enhancing regional risk management practices and pricing accuracy.

Finally, cost-sensitive ML, which considers varying costs for different types of errors, can also be identified as a promising avenue for future research.

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