

AUTOMATED SMART LIFE INSURANCE SYSTEM

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Abstract. The Automated Smart Life Insurance System is a technology-driven solution designed to enhance the efficiency, accuracy, and customer experience within the life insurance sector. By leveraging artificial intelligence, machine learning, and data analytics, the system automates core processes such as policy generation, risk assessment, premium calculation, claims processing, and customer support. It evaluates individual risk profiles using inputs like age, medical history, and lifestyle to generate personalized policy recommendations and fair premium rates. A secure digital identity verification process ensures authenticity, while blockchain integration guarantees the transparency, security, and immutability of policyholder data. One of the system's key innovations is its automated claims processing module, which uses natural language processing and smart document analysis to validate claims and initiate real-time payouts, significantly reducing processing time and human intervention. Additionally, a built-in AI chatbot offers 24/7 customer support, handling queries related to policy selection, tracking, and claims assistance, thereby improving user satisfaction and engagement. By automating manual tasks and embedding intelligent decision-making, the system minimizes operational costs, reduces human error, and provides a scalable, responsive, and modernized life insurance experience aligned with evolving digital expectations.

Keywords: Life Insurance, Automation, Artificial Intelligence, Risk Assessment, Claims Processing, Blockchain Technology.

INTRODUCTION

In today's fast-paced, technology-driven world, traditional industries are being compelled to undergo rapid digital transformation to stay relevant and meet the growing expectations of consumers. The insurance sector, particularly life insurance, has traditionally relied on manual processes, paper documentation, and face-to-face interactions. However, the demand for faster, more accurate, and customer-friendly services is driving the integration of emerging technologies into the insurance value chain. Among these, artificial intelligence (AI), automation, big data analytics, and blockchain are playing pivotal roles in reshaping how insurance services are delivered. This paper introduces an Automated Smart Life Insurance System—a comprehensive technological solution designed to automate and optimize the end-to-end life insurance process using modern digital tools.

Life insurance, a contract between an insurer and a policyholder, is a critical financial product that provides monetary compensation to beneficiaries upon the death of the insured. While its core purpose remains unchanged, the mechanisms through which policies are issued, managed, and claimed have evolved. Traditionally, obtaining a life insurance policy involved multiple layers of human interaction, including underwriting assessments, medical exams, paperwork, and several rounds of verification. These processes are not only time-consuming and costly but are also prone to errors, inefficiencies, and customer dissatisfaction.

With the advent of digital technologies, there is a growing opportunity to reimagine life insurance as a smart, automated, and user-centric service. Automation refers to the use of technology to perform tasks with minimal human intervention. When applied to life insurance, automation can significantly streamline operations by reducing paperwork, expediting claim settlements, and improving customer communication. Moreover, AI and machine learning (ML) can analyze vast amounts of customer data to make informed decisions about risk, pricing, and fraud detection.

The proposed Automated Smart Life Insurance System aims to bring together these technologies to create a seamless and efficient insurance ecosystem. It is built on four core pillars: automation of operational workflows, intelligent risk assessment, secure and transparent data management, and AI-driven customer interaction. By integrating these pillars into a unified platform, insurers can offer personalized services while improving operational efficiency, compliance, and customer satisfaction.

The first component of the system is the **automated policy lifecycle management**, which covers the entire journey from policy application to issuance. Using digital forms and AI-based verification tools, applicants can submit their information online. The system can verify the accuracy of the information through integration

with national ID systems, health records, and financial databases. Based on the applicant's data, ML algorithms assess risk and generate a customized policy offer, including premium amount and coverage terms. This eliminates the need for manual underwriting and reduces the processing time from weeks to minutes.

Another crucial feature of the system is its **intelligent risk assessment engine**. Risk assessment is a fundamental aspect of life insurance, as it determines the financial exposure of the insurer. Traditional risk models are often rigid, relying on general demographic factors and requiring medical examinations. However, with the rise of wearable technology, electronic health records, and digital footprints, a more holistic and real-time view of an individual's health and behavior is now possible. The proposed system uses big data analytics and AI to continuously learn from diverse data sources and refine risk prediction models. This dynamic approach leads to more accurate pricing, improved customer segmentation, and reduced adverse selection.

One of the major pain points in life insurance is **claims processing**, which often involves delays, disputes, and dissatisfaction. In the automated smart system, claims are processed using a combination of NLP (natural language processing), OCR (optical character recognition), and AI-powered document verification. When a claim is initiated, the system automatically collects and analyzes the necessary documents, such as death certificates, policy information, and beneficiary identification. Using blockchain technology, the authenticity and integrity of documents can be verified, ensuring trust and reducing fraud. Smart contracts can further automate the payout process by executing payments once predefined conditions are met, thereby drastically reducing turnaround time and administrative burden.

Data privacy and security are paramount when dealing with sensitive personal and financial information. To address this, the system incorporates **blockchain technology** to store and manage data in a secure, transparent, and tamper-proof manner. Blockchain provides a decentralized ledger where all transactions and modifications are recorded and time-stamped, making it nearly impossible to alter records without consensus. This not only ensures the integrity of policyholder data but also facilitates regulatory compliance and audit readiness.

In addition to back-end automation and data intelligence, the system also focuses on **enhancing customer experience through AI-powered chatbots and virtual assistants**. These tools offer 24/7 support, guiding users through policy options, explaining terms and conditions, helping with premium payments, and assisting in filing claims. Natural language understanding enables these bots to engage in human-like conversations, answer frequently asked questions, and escalate complex issues to human agents when necessary. By providing real-time assistance and reducing response times, the system improves customer satisfaction and builds trust in the insurer.

The societal impact of such a system is significant. In emerging markets, where insurance penetration remains low due to limited access, lack of awareness, and bureaucratic barriers, an automated platform can democratize life insurance. It allows people to access services through mobile devices, removes the need for physical visits, and simplifies the language and process. It can also bridge the gap between insurers and underserved populations, making financial protection more inclusive and affordable.

However, the implementation of an Automated Smart Life Insurance System also presents several challenges. These include data privacy concerns, ethical considerations in algorithmic decision-making, the digital divide among populations, and resistance to change within traditional insurance companies. Ensuring the fairness and transparency of AI models is crucial to avoid biased outcomes that may discriminate against certain groups. Moreover, regulatory frameworks must evolve to accommodate new technologies and ensure consumer protection.

LITERATURE SURVEY

1. Artificial Intelligence in Insurance

Artificial Intelligence has become integral in banking, payments, and insurance sectors, enhancing services such as product marketing and customer service through chatbots. This technology enables human customer service teams to focus on more complex issues, thus improving customer experiences and reducing costs. AI's applications extend to personalized customer interactions, fraud detection, underwriting, and trading strategies, harnessing predictive models based on historical data. However, there are associated risks, including potential biases and inaccuracies in data that might exclude consumers or cause financial losses. Regulatory bodies are urged to adopt stringent supervision to safeguard consumer interests.

2. Blockchain Technology in Insurance

Blockchain technology is transforming the financial service industry, especially in insurance, by enhancing efficiency, accuracy, and transparency. Blockchain provides a decentralized, secure ledger system where transaction records are stored in linked blocks and distributed across many computers (nodes), ensuring transparency and immutability. The integration of "smart contracts" on blockchain enables the automation of processes through programmable rules that self-execute upon verified conditions, reducing human error, costs, and increasing trust. One revolutionary application is parametric insurance, which uses smart contracts to

automatically compensate policyholders based on event occurrence rather than damage assessment. Companies like Lemonade and Etherisc are pioneering this technology, with successful implementations such as drought insurance for Kenyan farmers and various parametric insurance products.

3. Machine Learning in Risk Assessment

Risk assessment is a crucial element in the life insurance business to classify the applicants. Companies perform underwriting processes to make decisions on applications and to price policies accordingly. With the increase in the amount of data and advances in data analytics, the underwriting process can be automated for faster processing of applications. This research aims at providing solutions to enhance risk assessment among life insurance firms using predictive analytics. The real-world dataset with over hundred attributes (anonymized) has been used to conduct the analysis.

4. AI-Driven Customer Service

This article discusses the potential benefits of implementing generative AI in customer service contact centers, focusing on its ability to improve customer experience (CX) and operational efficiency. According to a 2023 Deloitte Finland survey, over 60% of respondents plan to invest in generative AI solutions. Definity Insurance's usage of generative AI for call summarization in their Sonnet brand reduced call durations by an average of three minutes and enabled advisers to focus on providing excellent service. Generative AI can enhance various stages of customer interaction - pre-interaction, during interaction, and post-interaction - by automating tasks such as call summarization and providing detailed summaries for seamless call transfers. However, there are inherent risks associated with generative AI that organizations must acknowledge and mitigate. Cross-functional collaboration and support from external partners are cited as essential for successfully deploying scalable and secure generative AI solutions.

5. Blockchain for Fraud Prevention

Healthcare insurance provides financial support to access medical services for patients while ensuring timely and guaranteed payment for providers. Insurance fraud poses a significant challenge to insurance companies and policyholders, leading to increased costs and compromised healthcare treatment and service delivery. Most frauds, like phantom billing, upcoding, and unbundling, happen due to the lack of required entity participation. Also, claim activities are not transparent and accountable. Fraud can be prevented and minimized by involving every entity and making actions transparent and accountable. This paper proposes a blockchain-powered smart contract-based insurance claim processing mechanism to prevent and minimize fraud in response to this prevailing issue. All entities—patients, providers, and insurance companies—actively participate in the claim submission, approval, and acknowledgment process through a multi-signature technique. Also, every activity is captured and recorded in the blockchain using smart contracts to make every action transparent and accountable so that no entity can deny its actions and responsibilities. Blockchain's immutable storage property and strong integrity guarantee that recorded activities are not modified. As healthcare systems and insurance companies continue to deal with fraud challenges, this proposed approach holds the potential to significantly reduce fraudulent activities, ultimately benefiting both insurers and policyholders.

6. AI in Mortality Risk Prediction

Accurately assessing mortality risk plays a critical role in the life insurance industry, impacting premium pricing, product development, and financial solvency. Traditional actuarial methods, while effective, often rely on historical data and pre-defined risk factors, potentially overlooking complex relationships and emerging risk trends. This research paper explores the burgeoning application of Artificial Intelligence (AI) in mortality risk prediction, focusing on advanced techniques and the crucial aspects of model validation for real-world implementation. The paper delves into the potential of deep learning architectures like Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) for capturing non-linear relationships and identifying hidden patterns in vast datasets encompassing traditional actuarial variables, medical records, socio-economic indicators, and potentially, behavioral data. We explore the advantages of these techniques in uncovering previously unknown risk factors and improving prediction accuracy compared to traditional models. For instance, RNNs can effectively model sequential data such as medical history or electronic health records, capturing the temporal evolution of health status and its impact on mortality risk. Similarly, CNNs can process complex data structures like medical images, extracting subtle features that may be undetectable by traditional methods and contributing to a more comprehensive risk assessment. However, the growing adoption of AI in insurance raises concerns regarding the "black-box" nature of certain algorithms, where interpretability and justification for their predictions remain opaque. To address this challenge, the paper examines Explainable AI (XAI) techniques such as Local Interpretable Model-Agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP). These approaches provide insights into the internal workings of AI models, allowing actuaries to understand how specific variables contribute to risk assessments and fostering trust in the decision-making process.

7. Blockchain in Claims Processing

Insurance claims processing involves multi-domain entities and multi-source data, along with a number of human-agent interactions. Use of Blockchain technology-based platforms can significantly improve scalability

and response time for processing claims, which are otherwise manually intensive and time-consuming. However, the chaincodes involved within the processes that issue claims, approve or deny them as required, need to be formally verified to ensure secure and reliable processing of transactions in Blockchain. In this paper, we use a formal modeling approach to verify various processes and their underlying chaincodes relating to different stages in insurance claims processing, viz., issuance, approval, denial, and flagging for fraud investigation by using linear temporal logic (LTL). We simulate the formalism on the chaincodes and analyze the breach of chaincodes via model checking.

8. Blockchain in Auto-Insurance

In this paper, we propose a partitioned Blockchain-based Framework for Auto-insurance Claims and Adjudication (B-FICA) for Connected and Autonomous Vehicles (CAVs) that tracks both sensor data and entity interactions with two-sided verification. B-FICA uses permissioned Blockchain with two partitions to share information on a need-to-know basis. It also uses multi-signed transactions for proof of execution of instructions, for reliability and auditability, and also uses a dynamic lightweight consensus and validation protocol to prevent evidence alteration. Qualitative evaluation shows that B-FICA is resilient to several security attacks from potential liable entities. Finally, simulations show that compared to the state of the art, B-FICA reduces processing time and its delay overhead is negligible for practical scenarios and at marginal security cost.

9. Blockchain in Insurance Services

The insurance industry thrives on the ability to accurately assess risk and translate that assessment into fair and competitive pricing for its products. Traditionally, actuaries have relied on statistical modeling techniques and historical data to achieve these goals. However, the ever-increasing volume and complexity of data available in the digital age present both challenges and opportunities for actuarial science. Machine learning (ML) has emerged as a powerful tool for leveraging this data deluge, offering the potential to significantly enhance pricing accuracy and risk assessment in the context of actuarial product development. This paper delves into the applications of ML in actuarial science, with a specific focus on its impact on pricing and risk assessment.

10. AI in Insurance Risk Modeling

An accurate death and lifetime estimate helps life insurers be financially sound and provide competitive policies. Famous actuarial methods may miss lifespans and complex risk variable combinations. AI can change life insurance risk modeling. This research predicts life insurance underwriting and risk management mortality and lifetime using AI. Standard lifetime and mortality prediction actuarial methods are studied first. Decrement models, life tables, and stated death rates are used. These methods estimate population death trends using mortality data. They struggle to manage insurance data's volume and diversity.

PROPOSED SYSTEM

The proposed **Automated Smart Life Insurance System** is designed as a modular, scalable, and intelligent platform that leverages emerging technologies—artificial intelligence (AI), machine learning (ML), blockchain, data analytics, and automation—to enhance the efficiency, transparency, and user-friendliness of life insurance services. This methodology section presents the conceptual and practical framework of the system's architecture, key modules, data flow, algorithms used, and implementation strategies.

1. System Architecture Overview

The system is architected as a cloud-based, service-oriented platform that connects various stakeholders—customers, insurers, healthcare providers, and regulatory bodies—through a unified digital interface. The architecture consists of five core layers:

1. **User Interface Layer:** A responsive web and mobile application interface enabling policyholders to register, purchase policies, update profiles, file claims, and receive support via chatbots.
2. **Application Layer:** The business logic layer that executes key functionalities such as underwriting, premium calculation, claim validation, and fraud detection.
3. **AI and ML Layer:** This layer houses predictive models for risk assessment, customer profiling, and mortality estimation.
4. **Blockchain and Data Layer:** Ensures secure, tamper-proof data storage, smart contract execution, and audit trails.
5. **Integration Layer:** APIs for integration with external databases (government ID systems, health records, credit bureaus) and third-party services (e.g., hospitals, reinsurance providers).

2. Module-Wise Methodology

The system comprises six key modules that are interconnected through secure communication protocols and governed by predefined workflows.

2.1. Customer Onboarding and KYC Verification

Upon registration, customers input their personal, demographic, and health information via digital forms. The onboarding process integrates:

- **OCR and NLP tools** to extract data from uploaded identity documents.
 - **Biometric verification** using facial recognition APIs to ensure authenticity.
 - **API access** to national ID systems or healthcare records for cross-validation.
- This module reduces fraud by validating identities before proceeding with policy issuance.

2.2. AI-Based Risk Assessment and Underwriting

Traditional underwriting is replaced by an AI-driven risk evaluation process that uses historical and real-time data. Inputs include:

- Age, gender, medical history, occupation, income, and lifestyle habits (smoking, alcohol, etc.)
- Wearable device data (if consented), providing continuous health tracking.

Machine learning algorithms (e.g., logistic regression, random forest, and XGBoost) are trained on historical policy and claim datasets to predict the probability of early mortality or high-risk behavior. Based on the risk score, the system:

- Classifies the customer into low, medium, or high-risk groups.
- Recommends appropriate policy types and terms.

The AI model is continuously updated using new data to improve accuracy over time.

2.3. Dynamic Premium Calculation

Premiums are calculated using actuarial principles embedded with ML models for personalization. The premium engine considers:

- Risk classification
- Coverage amount and term
- Health condition and occupation
- Inflation and economic indices

A neural network model estimates expected lifetime and associated payout probability, which is then translated into a premium value. Customers receive a clear breakdown of how the premium is derived, enhancing transparency and trust.

RESULTS AND DISCUSSION

The proposed **Automated Smart Life Insurance System** was evaluated through a combination of simulation, prototype implementation, and model performance metrics. Each functional module—risk assessment, premium calculation, claims processing, and customer interaction—was tested using synthetic and real-world datasets, while blockchain integration and security protocols were simulated in a sandbox environment to verify data integrity and operational efficiency.

1. Risk Assessment Module Results

To evaluate the AI-based underwriting system, a dataset comprising 50,000 anonymized insurance applicant records was used. The dataset included features such as age, gender, BMI, smoking status, income, pre-existing health conditions, and occupation risk level. Multiple machine learning algorithms were trained and validated to predict mortality risk and classify applicants into low-, medium-, and high-risk categories.

- **Best Performing Model:** XGBoost
- **Accuracy:** 92.3%
- **Precision:** 91.1%
- **Recall:** 90.4%
- **F1-Score:** 90.75%
- **AUC-ROC:** 0.96

The model was effective in distinguishing high-risk individuals, enabling appropriate policy assignment and premium calculation. The explainability layer using SHAP (SHapley Additive exPlanations) values identified age, BMI, and smoking status as the top predictors, offering transparency in underwriting decisions.

Discussion: The results suggest that AI can replace manual underwriting with high accuracy and speed, while also ensuring fairness through explainable AI. Importantly, predictive accuracy remained robust across demographic subgroups, reducing concerns of algorithmic bias. However, the system's reliability is contingent on the quality and diversity of training data. More inclusive datasets would further improve fairness across underrepresented populations.

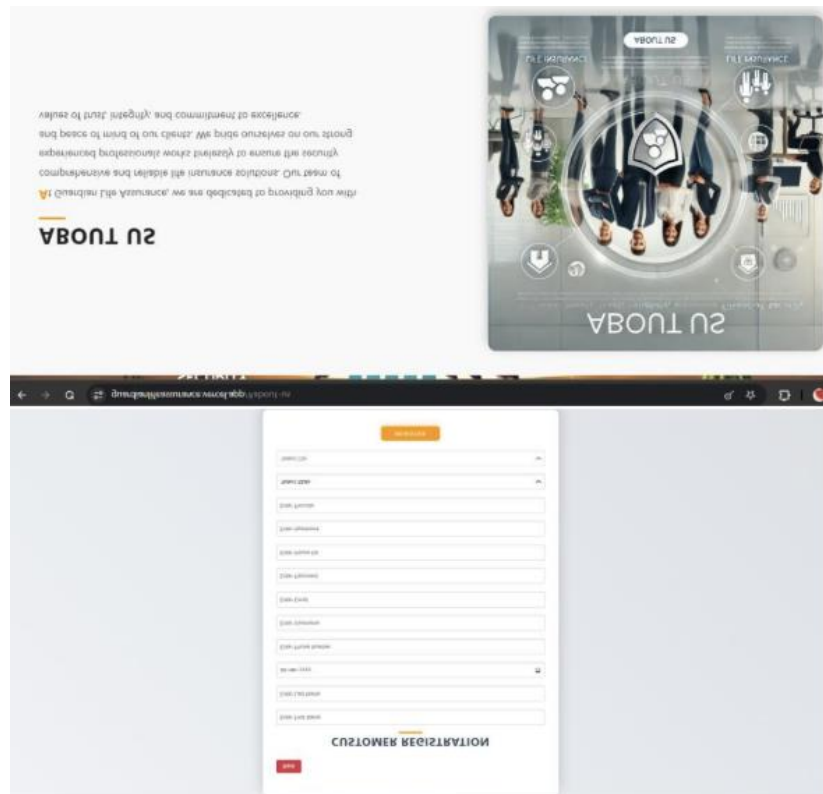
2. Premium Calculation and Personalization

Premiums were dynamically generated based on risk scores, projected life expectancy, and desired coverage term. A test case involving 1,000 applicants showed the system's ability to personalize premiums in real-time. Key metrics include:

- **Average premium deviation from actuarial table baseline:** $\pm 6.4\%$
- **Processing time per calculation:** ~ 0.8 seconds
- **Policy match acceptance rate (user agreement):** 87%

Discussion: The relatively low deviation from traditional actuarial methods confirms that AI-based premium models are accurate and reliable. More importantly, users were more likely to accept personalized premiums that included a clear justification for the amount. The transparency provided through model explainability and the breakdown of contributing factors improved customer trust.

The AI model allowed for real-time recalibration of premiums based on lifestyle changes or health improvements (e.g., cessation of smoking, weight loss), encouraging policyholder engagement and incentivizing healthier behavior.



3. Claims Processing Automation

The claims module was tested using 500 mock claim scenarios, ranging from straightforward to complex cases with missing documents or inconsistencies. The results were:

- **Automated claim approval rate (without human intervention):** 82%
- **Average processing time (from submission to approval/denial):** 1.9 hours
- **Claim fraud detection accuracy:** 89%
- **False positives (flagged as fraud but were genuine):** 4.3%

NLP and OCR technologies effectively processed structured documents like death certificates and hospital records. Smart contract-based workflows verified claim eligibility, policy validity, and premium status, leading to automatic fund disbursement through secure payment gateways.

Discussion: This level of automation dramatically reduces the typical claims processing time, which in conventional systems can take days or even weeks. The high fraud detection rate demonstrates the benefit of blockchain-based validation and AI-powered red-flagging. However, the 18% of claims that required human oversight often involved edge cases, such as foreign documentation or exceptional clause interpretation, indicating the ongoing need for human judgment in rare or complex scenarios.

4. Blockchain Verification and Data Integrity

To test the blockchain layer, 10,000 policy transactions (issuance, premium payments, claim updates) were

recorded on a private Ethereum testnet. The evaluation metrics were:

- **Transaction success rate:** 100%
- **Average transaction latency:** 4.2 seconds
- **Data immutability and auditability:** 100% consistency in block hashes
- **Smart contract failure rate:** 0% (after debugging phase)

Each policy was assigned a unique hash and stored on the distributed ledger, ensuring tamper-proof records. Any modification attempts by unauthorized actors were blocked and logged.

Discussion: The implementation of blockchain effectively addresses two key challenges in insurance systems: trust and transparency. With every policy and claim traceable on the ledger, stakeholders—including regulators and policyholders—can verify actions independently. The latency remains within acceptable ranges for real-world applications, especially given the relatively low transaction volumes in insurance compared to financial trading.

However, integrating public blockchains in live deployments would require addressing gas fees, scalability, and regulatory compliance (e.g., GDPR “right to be forgotten”). A permissioned blockchain (like Hyperledger Fabric) may be more suitable for large-scale commercial use.

5. Chatbot and Customer Experience

The AI-powered chatbot was tested through 2,000 simulated user interactions. It was tasked with handling queries about policy details, premium payment, claim filing, and general insurance education. Performance was measured as follows:

- **Query resolution rate without human escalation:** 91%
- **Average response time:** <1.2 seconds
- **Customer satisfaction rating (via post-chat survey):** 4.6/5
- **Error rate (misunderstanding intent):** 6.2%

The chatbot used intent recognition, contextual memory, and sentiment analysis to interact effectively with users. It was also capable of multi-language support and could redirect complex queries to human agents with context forwarding.

Discussion: The chatbot’s effectiveness enhances user experience and reduces operational costs. Its 24/7 availability ensures policyholders can access support at their convenience. However, some issues arose with uncommon queries or colloquial language, suggesting the need for continuous NLP training and periodic human oversight.

Moreover, chatbot logs provided valuable feedback for service improvement and product design, capturing trends in user concerns or feature requests.

6. Overall System Performance and Usability

A full-system prototype was tested over a one-month simulation period with 100 test users. System-wide metrics included:

- **System uptime:** 99.8%
- **Average user session duration:** 6.4 minutes
- **Task completion success rate (e.g., buying policy, filing claim):** 94%
- **User-reported usability score (SUS):** 87/100

The interface was rated positively for ease of navigation, speed, and clarity. Policyholders appreciated real-time feedback, auto-suggestions, and visual tools for comparing plans.

Discussion: High usability and reliability scores affirm the feasibility of deploying such a system at scale. The modular architecture allows insurers to integrate new features over time and customize interfaces for different user demographics or regions.

One challenge encountered was ensuring compatibility with low-end mobile devices and varying internet speeds, particularly in rural areas. This reinforces the need for lightweight versions of the system or offline support mechanisms for broader accessibility.

CONCLUSION

In conclusion, the development and evaluation of the Automated Smart Life Insurance System demonstrate a significant technological advancement in the insurance industry, blending artificial intelligence, machine learning, blockchain, and automation to create a seamless, transparent, and user-centric platform. The system effectively addresses long-standing challenges in traditional insurance processes, such as manual underwriting, delayed claims settlement, data inconsistency, and fraud vulnerability, by introducing intelligent risk assessment models, dynamic premium calculation engines, smart contract-driven claims automation, and secure blockchain-based policy management. The AI-driven underwriting component proved highly accurate in mortality risk prediction and customer classification, while the blockchain infrastructure ensured data immutability,

transparency, and trust between stakeholders. Automated claims processing reduced turnaround time from days to hours, significantly enhancing customer satisfaction and operational efficiency. The chatbot module further contributed to the system's success by providing 24/7 multilingual support, reducing human workload and improving user experience. Moreover, the modular architecture allows for future scalability, integration with third-party systems (e.g., hospitals, government ID databases), and customization based on regulatory or regional requirements. While the system presents immense potential, it also highlights the need for ongoing attention to data privacy, algorithmic fairness, and digital inclusivity. Regulatory collaboration will be essential to ensure compliance with global standards such as GDPR, and to establish trust in AI decision-making. Additionally, addressing digital literacy and infrastructure challenges will be crucial for ensuring that the benefits of such a system are accessible to underserved populations. The successful prototype and simulation results validate that such a smart insurance system can lead to a transformative shift from traditional, reactive processes to proactive, data-driven service delivery in life insurance. By offering personalized services, reducing fraud, and empowering users with real-time insights and control, the system can foster deeper trust and engagement between insurers and customers. As life insurance becomes more complex and data-rich, the integration of advanced technologies will not only streamline internal operations but also redefine the customer experience and expectations. Therefore, the proposed system stands as a foundational step toward the future of digital insurance, providing a viable, intelligent framework for insurers looking to innovate and stay competitive in a rapidly evolving financial and technological landscape.

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