Smart LIC Recommendation System

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ABSTRACT

Choosing the right insurance policy can often feel confusing because of the wide variety of plans and complex terms involved. Many people end up picking policies that don't fully match their needs, leading to either unnecessary expenses or inadequate coverage. The LIC Policy Recommender System aims to solve this problem by giving users personalized recommendations based on their details like age, investment budget, policy duration, smoker status, and health requirements. The system uses a simple machine learning model, stores customer information securely, and presents the results through an easy-to-use interface. It also allows users to see direct links to official policy pages and compare estimated premiums visually. This makes the decision-making process faster, more reliable, and less dependent on agents or manual research.

Keywords: Insurance Policies, Policy Recommendation, LIC, Personalized System, Machine Learning, Customer Assistance

1. INTRODUCTION

Insurance is widely recognized as an essential tool for managing risk and ensuring long-term financial stability, yet many individuals face significant barriers in identifying the right plan for their needs. Conventional policy selection methods often involve interacting with agents, reading lengthy brochures, or navigating through static online listings, all of which require time, effort, and a fair level of understanding of insurance terms. These approaches typically provide general recommendations that may not reflect the personal requirements of each user.

As a result, many individuals purchase plans that either do not provide adequate coverage or exceed their financial capacity, leading to dissatisfaction or underutilization of benefits. In response to these challenges, the LIC Policy Recommender System has been designed as a digital, user-focused solution. This system enables customers to easily register, input their details, and receive recommendations tailored to their specific financial and personal profile. By employing a machine learning model to analyze and map user inputs to the most relevant policies, it ensures that each recommendation is meaningful and practical. Furthermore, the system integrates interactive elements, such as graphical premium comparisons and direct access to official LIC policy pages, which reduce confusion and support informed decision-making. The primary objective of this system is to transform the insurance selection process from a manual, agent-driven model to an intelligent, user-controlled experience that aligns with modern digital trends.

2. LITERATURE SURVEY

The concept of recommendation systems has evolved significantly over the past decade, finding applications in industries such as e-commerce, entertainment, and education. In these domains, recommendation engines help users make choices by analyzing past interactions, preferences, and patterns. The insurance sector, however, has been comparatively slower in adopting personalized recommendation technology, primarily relying on basic filtering mechanisms or agent-led advice. Early models in the insurance industry were largely rule-based, where users would receive policy suggestions according to fixed criteria like age brackets or general income groups. While helpful to some extent, these approaches lacked depth and failed to consider multiple influencing factors, such as investment range, policy duration, or health requirements. Recent research highlights the growing potential of machine learning in addressing these limitations. Algorithms such as K-Nearest Neighbors (KNN), decision trees, and collaborative filtering models have been tested for policy recommendation systems, with encouraging results in terms of accuracy and user satisfaction. Studies have also emphasized the importance of visual aids and interactive dashboards in helping customers interpret recommendations more effectively. Despite these advancements, a gap remains in implementing such systems with full integration—covering customer registration, policy databases, real-time recommendation, and official policy access—while maintaining simplicity for end-users. This research builds upon these findings by proposing a system that combines machine learning with secure data handling and a user-friendly graphical interface to deliver a holistic policy recommendation experience.

3. EXISTING SYSTEM

The existing landscape of insurance advisory primarily relies on traditional mechanisms, where customers either consult agents or explore static online platforms to gather policy information. While these methods have been in place for years, they come with several inherent shortcomings. Agent-driven processes often result in biased recommendations, as agents may prioritize policies with higher commissions over the actual needs of the customer. Static websites, on the other hand, provide a large repository of policies but lack intelligent filtering capabilities. Users are expected to browse through extensive lists, read detailed documents, and manually compare features such as premiums, terms, and eligibility criteria. This not only consumes time but also creates confusion, particularly for first-time policy buyers or those with limited understanding of financial planning. Moreover, most existing systems fail to offer real-time feedback or dynamic updates based on user inputs. The data collected, if any, is rarely utilized to provide actionable insights or personalized pathways. Another limitation is the lack of secure customer management, where user information is often not stored or validated properly, leading to repeated entries or inconsistent experiences. Overall, the current methods emphasize administrative management rather than personalized advisory, leaving a significant gap for solutions that can intelligently match individual requirements with the vast range of available policies.

4. PROPOSED SYSTEM

To address the limitations of existing methods, the proposed LIC Policy Recommender System introduces a structured, technology-driven approach to policy selection. At its core, the system is designed to collect essential user details—such as full name, email, mobile number, location, age, monthly investment, policy term, smoker status, and health check requirements—and use these parameters to generate a ranked list of recommended policies. The machine learning algorithm employed, K-Nearest Neighbors (KNN), enables the system to identify policies most similar to the user's profile based on historical policy data.

In addition to personalized recommendations, the system incorporates a secure registration and login mechanism to ensure that each user's data is recorded accurately and duplicates are prevented. The interface, built using Tkinter, is designed for simplicity and accessibility, featuring clear input forms, intuitive navigation, and interactive buttons for exploring policy details. Visual graphs further support decision-making by displaying estimated premiums across different recommended policies, helping users quickly compare costs and terms. Direct integration with official LIC policy links ensures that users have access to verified and up-to-date information without navigating multiple websites. By combining machine learning, database management, and interactive design, the proposed system simplifies the insurance selection process, reduces the need for agent dependency, and empowers users to make better-informed decisions in less time.

5. METHODOLOGY

The development of the LIC Policy Recommender System followed a structured methodology to ensure accurate recommendations, secure user management, and a seamless user experience. Each phase of the methodology contributed to building a system capable of suggesting policies tailored to individual needs.

1. Data Collection

The first step involved collecting and preparing a comprehensive dataset of LIC insurance policies. The dataset included essential parameters such as minimum and maximum eligible age, monthly premium, policy term duration, smoker status, and health check requirements. This data was gathered from open resources and structured in a CSV format to ensure compatibility with machine learning tools. Each policy entry provided the baseline for creating personalized recommendations for users.

2. Data Preprocessing and Preparation

Before feeding the data into the machine learning model, several preprocessing steps were carried out to enhance accuracy and maintain consistency:

- ✓ **Data Cleaning**: Missing numerical values were filled using mean imputation, and missing categorical values were replaced with the mode.
- ✓ **Encoding**: Categorical attributes such as smoker requirement and health check requirement were encoded numerically using Label Encoding to make them machine-readable.
- ✓ **Feature Scaling**: Numerical fields like age limits, monthly premium, and policy term were scaled using StandardScaler to bring them into a uniform range for the recommendation model.
- ✓ **Data Validation**: Inconsistent or incomplete entries were removed to improve dataset reliability.

3. Model Training (K-Nearest Neighbors)

The core of the system relies on a K-Nearest Neighbors (KNN) model for policy recommendation. This algorithm was chosen due to its simplicity, efficiency, and effectiveness in matching user profiles to existing policies based on similarity. The cleaned and scaled dataset was used to train the KNN model to identify the ten most relevant policies for a given user input. This model was validated using test cases to ensure logical and accurate recommendations.

4. Backend Development (Python + SQLite)

The backend of the system was built in Python, integrating both the machine learning model and the database. SQLite was used to handle customer registration and login securely. Key backend functionalities included:

- ✓ Storing customer details (name, email, mobile, location).
- ✓ Checking for duplicate registrations based on email or mobile number.
- ✓ Processing user inputs such as age, monthly investment, and policy term.
- ✓ Passing the processed data through the trained KNN model.
- ✓ Returning the list of recommended policies with estimated premiums and terms.

5. Frontend Development (Tkinter)

A user-friendly graphical interface was developed using Python's Tkinter library. The interface included:

- ✓ **Registration and Login Screens** to manage user access.
- ✓ **Profile Input Window** where users could enter their age, investment capacity, smoker status, health check requirement, and policy term.
- ✓ **Recommendation Window** displaying the top policies in a scrollable view, each with policy details and direct links to official LIC websites.
- ✓ **Graphical Visualization Feature** for comparing premium amounts across recommended policies.

System Workflow

- ✓ The overall process flow of the system is as follows:
- ✓ A new user registers or an existing user logs in.
- ✓ The user enters their personal details and preferences.

- ✓ The system validates the inputs and scales them according to the trained model parameters.
- ✓ The processed data is passed to the KNN model, which identifies the closest matching policies.
- ✓ The system displays the top recommendations along with estimated premiums and provides links to explore further details.
- ✓ Users can view a premium comparison graph or restart the process to modify their inputs.

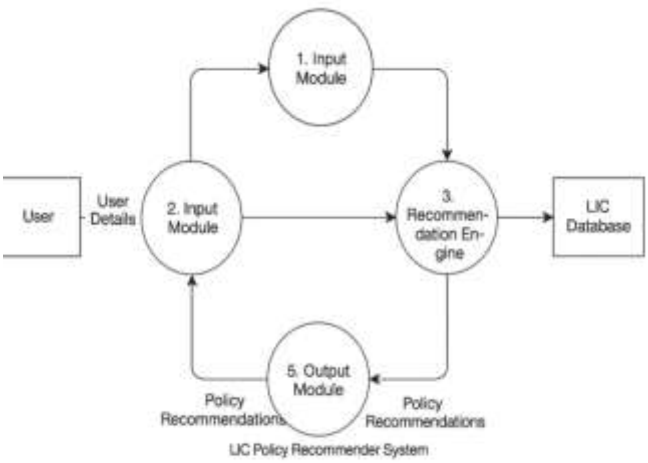
6. IMPLEMENTATION

The architecture of the LIC Policy Recommender System has been carefully designed to create a seamless link between user inputs, policy datasets, and intelligent recommendations. It follows a structured, modular design consisting of three main components: the data management layer, the recommendation engine, and the user interface. The data management layer is responsible for handling all policy-related data and storing user details securely using a lightweight SQLite database. This database stores essential information such as names, emails, mobile numbers, and locations, ensuring that returning users can log in without re-entering their details while preventing duplicate registrations. In addition to managing customer records, this layer also includes a cleaned and preprocessed LIC policy dataset containing important fields like eligible age ranges, premium amounts, policy terms, smoker requirements, and health check details. Any missing or inconsistent data within this dataset is managed using techniques such as mean or mode substitution to maintain data integrity.

At the core of the system lies the recommendation engine, which applies a K-Nearest Neighbors (KNN) algorithm to generate policy suggestions that closely align with user preferences. When a user submits their profile—consisting of age, monthly investment capacity, desired policy term, smoker status, and health check requirement—the system validates the data to ensure it falls within acceptable limits. These values are then normalized using the same scaling factors applied during model training, ensuring consistency and accuracy across the dataset. The KNN model compares the input against existing policies, identifies the most relevant ones, and prepares a ranked list of recommendations. This ensures that the user receives the top ten policies best suited to their financial goals and lifestyle.

The user interface forms the third critical component of the system and is designed using Python’s Tkinter library to ensure simplicity and accessibility. Users can easily navigate between registration, login, and recommendation windows. After entering their preferences, they are presented with a clear, scrollable list of recommended policies, each displaying key details such as policy ID, estimated premium, and term duration. Direct web links to the official LIC pages are also included, enabling users to explore policy documents without searching separately. A premium comparison graph further enhances the experience by allowing users to visually analyze and compare costs across the suggested policies.

In addition to its main functions, the system also incorporates robust error handling and basic security measures. It validates user inputs, prevents invalid registrations, and handles database exceptions gracefully to avoid interruptions. Duplicate checking ensures that user data remains consistent, while informative error messages guide users in case of incorrect inputs. Sensitive customer details are stored in a controlled environment to maintain privacy. This layered architecture not only ensures accuracy and efficiency in policy recommendations but also makes the system reliable, user-friendly, and adaptable for future upgrades, such as mobile app integration, multilingual support, or enhanced machine learning techniques.



7. CONCLUSION

The development of the LIC Policy Recommender System marks a step forward in the modernization of insurance policy advisory services. By combining machine learning, structured data handling, and an interactive graphical interface, the system addresses the major challenges faced by individuals in selecting suitable insurance plans. It enables users to explore multiple policies based on their unique profile and offers clear, actionable recommendations that improve both confidence and convenience in decision-making. Unlike traditional approaches that are often agent-driven or static, this system empowers users to take control of their financial planning journey. Its modular architecture ensures that it can be scaled, enhanced, or integrated with additional services in the future, making it a sustainable solution for evolving customer needs. The incorporation of features like premium visualization, secure registration, and direct policy links further strengthens its value as a digital advisory platform.

While there are areas for future improvement, the current system already demonstrates the potential to reduce decision fatigue, improve insurance literacy, and create a more transparent selection process for LIC customers.

8. FUTURE ENHANCEMENT

While the current version of the LIC Policy Recommender System provides an effective framework for personalized policy selection, several enhancements could make it more powerful and versatile. One possible upgrade is the integration of advanced machine learning models, such as Random Forest or Gradient Boosting, which may improve the accuracy of recommendations by considering more complex interactions between user inputs and policy attributes.

Another improvement involves the development of a mobile-friendly version of the system to provide on-the-go access, complete with push notifications for policy updates, renewals, and premium reminders. Multilingual support could make the platform more inclusive, particularly for regions with diverse language preferences. Gamification elements, such as progress indicators or rewards for completing financial planning milestones, could be introduced to encourage user engagement. Additionally, incorporating chatbot-based assistance could guide users through the process interactively, addressing queries in real-time. From a data management perspective, features like premium payment tracking, renewal history, and federated data learning could make the system even more comprehensive and privacy-conscious. These enhancements would ensure that the system remains relevant, user-friendly, and adaptable to the changing landscape of digital insurance advisory.

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