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A Fuzzy-Based Framework for Personalized Health Insurance Premium Calculations

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Abstract- The insurance sector is constantly moving towards personalized services, which means that new ways of determining rates are required. In this research, we offer a fuzzy logic-based system for determining individual insurance rates. To improve the accuracy and fairness of premium assessments, this approach makes use of fuzzy logic. When processing input variables, the framework takes into account a wide range of dynamic parameters, such as age, insurance claim history, yearly income, and credit score. Because of the inherent imprecision and uncertainty in real-world data, the membership functions for these input variables have been meticulously built. There has been an intentional use of triangles and trapezoids. The intricate interplay between input data and the desired personalized insurance premiums can be represented by fuzzy rules. Due to its ability to account for varying levels of premium category membership, the framework facilitates an all-encompassing decision-making process. Full testing and comparison with industry-standard methods of premium computing are required to prove the proposed framework's viability. The results show that individuals' risk profiles can be accurately and fairly adapted to when determining insurance prices. In addition, while running, the fuzzy logic system can adjust to new client attributes and shifting market circumstances. By presenting a Fuzzy-Based Framework more adapted to the complex nature of real-world risk variables; this research contributes to the improvement of tailored insurance services. Not only does the suggested method improve the precision of premium estimates, but it also encourages openness and increases customer happiness.

Keywords: Fuzzy Logic, Insurance Premium, Personalization, Risk Assessment, Claim History, Credit Score, Annual Income.

1. Introduction: New methods of precisely determining risk profiles of specific customers and charging them premiums in accordance with those assessments are urgently needed in the insurance industry, which is seeing a tremendous shift towards personalized services. Conventional approaches to insurance rate calculation depend on rigid algorithms that fail to adequately capture the intricacies and uncertainties surrounding consumers' changing characteristics. To tackle this problem, we suggest utilizing a Fuzzy-Based Framework for individualized insurance premium estimations. This approach uses fuzzy logic to make premium evaluations more fair and accurate. A more flexible and adaptable approach to decision-making, fuzzy logic provides a reliable way to capture the inherent ambiguity and imprecision in real-world data. Age, annual income, claim history, and credit score are some of the input parameters that this model considers. A membership function, be it trapezoidal or triangular, is painstakingly constructed to reflect each of these elements. The system is able to comprehend the nebulous and unexpected traits of specific risk factors thanks to these procedures. So, instead of the typical exact logic, the system can provide a more complex representation. The foundation of our research is the development of fuzzy rules that can capture the intricate links between input data and personalized insurance premiums.

These regulations are designed to be flexible enough to adjust to ever-changing market conditions and customer preferences. As a result, we have a premium determination technique that is both flexible and responsive. When it comes to premium categories, our method simplifies things by taking into account the various membership tiers. The result will be a premium calculation method that prioritizes the needs of our clients while also being open and transparent. Our proposed framework has been rigorously tested to ensure its efficacy. We evaluate our fuzzy logic system's premium calculation performance in comparison to that of more conventional methods in these experiments. We bring in a new era of personalized insurance options with the preliminary data that prove our approaches are incredibly precise and objective. Improving the accuracy of premium computations is not the only consequence of this discovery. By advocating transparency and equality, our method satisfies the growing need of clients for equitable and personalized insurance solutions.

Baser and Apaydin (2010) proposed a strategy for working out protection guarantee saves utilizing half breed fuzzy least-squares relapse examination. They looked at the outcomes from old style strategy and delicate figuring approach by involving unique information in car obligation protection. Kumar and Jain (2012) introduced a model which depends on fuzzy master framework that will help insurance agency to figure out the mortality of guarantor in the presence of diabetes for life coverage guaranteeing. Jain (2013) investigated present and past status of LI area and furthermore examines about the future methodologies of the Indian protection area. Khodamoradi et al. (2014) have looked at a variety of Iranian insurance companies and proposed a new hybrid method that combines the DEMATEL and PROMETHEE II methods with sample data from insurance companies that were listed.

Mutaliba et al. (2016) applied that these blend strategies were applied in our model which is appropriate for Malaysian populace overall. Ertugrul and Oztas (2018) introduced the end of disparities and the foundation of more pleasant charge framework that gives an interdisciplinary point of view about the overall health care coverage. A decision support model (DSM) was suggested by Susanto and Utama (2022) to assess claim cases, identify claim risk categories (CRCs) and make claim decisions. In the event that an insurance claim is approved, Utama and Susanto (2023) created a computational decision model that relies on service technology. Insurance claims, policy administration, and AHP are three types of other applications that are interdependent with the model application. All of the apps were able to talk to each other using eight SOA-based services.

2. Methodology: An adaptive and dynamic approach to evaluating health insurance costs is offered by the projected premium values that comprise a fuzzy-based framework for individual health insurance premium computations. Incorporating vague or inaccurate data is now within reach thanks to fuzzy logic, a mathematical framework. Fuzzy logic framework involves fuzzy sets, fuzzy rules, fuzzy inference system, fuzzification, decision making and defuzzification process. This paves the way for a more nuanced and tailored examination of the factors that impact health insurance premiums. Several input factors are considered by a method in this scenario to determine the estimated values of insurance premiums. Factors such as age, insurance claim history, health issues and credit score are included in this category. The fact that subjective and qualitative information can be conveyed linguistically allows for its incorporation into decision-making. The fuzzy logic framework takes input variables and uses them to calculate the expected output, in this case the health insurance premium, in accordance with a predetermined set of rules. The factors that impact insurance rates are complicated and often subjective; these principles reflect the knowledge of domain experts and address this.

3. Membership function plot of input and output variables: In order to calculate individual health insurance premiums, a Fuzzy-Based Framework relies on the plot of the membership function. Fuzzification and defuzzification are shown figures for each input and output variable, highlighting the linguistic uncertainty inherent in fuzzy logic. Stakeholders, including insurers and policyholders, can benefit from this visual tool's improved comprehension of the level of membership or contribution of a certain value to a fuzzy set. In context of personalized health insurance such as their factors age (A), insurance claim history (ICH), health issues (HI) and credit score (CS) are show in figures 1 to 4 and health insurance premium (HIP) show in figure 5. The membership function picture is used to show how to take numerical input values and convert them to linguistic values. Then, from fuzzy output values, we can get clear and actionable results for calculating health insurance premiums.

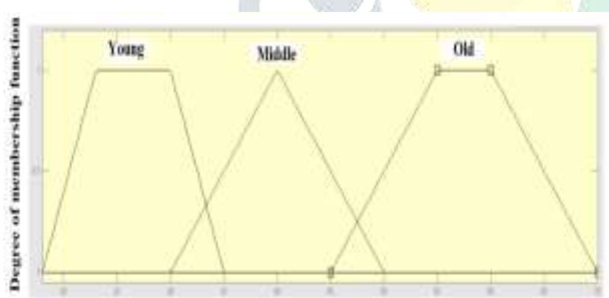

Figure 1: Membership function for age (input variable)

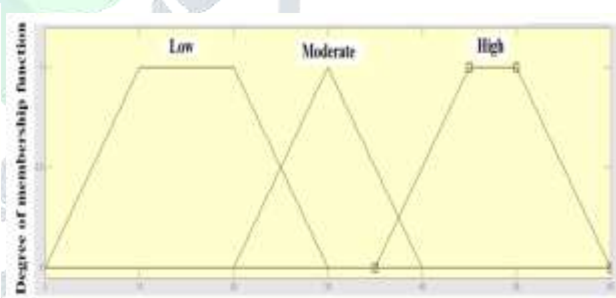

Figure 2: Membership function for insurance claim history (input variable)

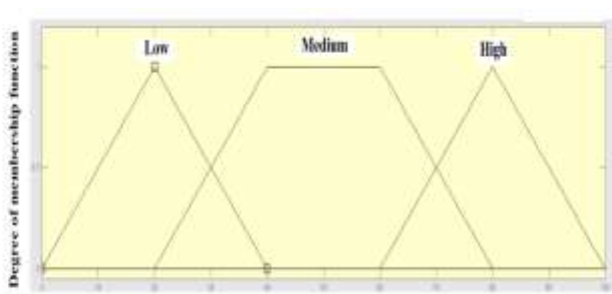

Figure 3: Membership function for health issues (input variable)

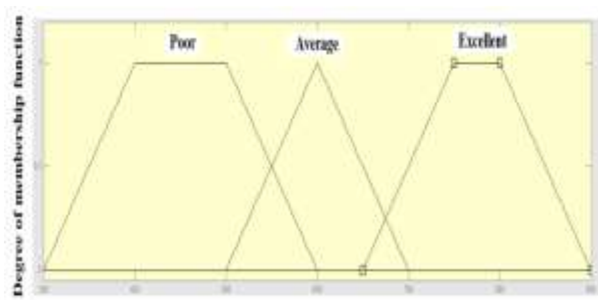

Figure 4: Membership function for credit scores (input variable)

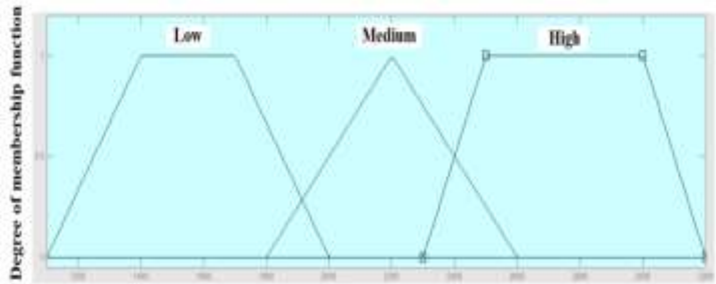

Figure 5: Membership function for health insurance premium (output variable)

The corresponding membership functions are:

$$\mu_{young}^{A}(x_1) = \begin{cases} \frac{x_1-18}{5} & 18 \le x_1 \le 23 \\ 1 & 23 \le x_1 \le 30 \\ \frac{35-x_1}{5} & 30 \le x_1 \le 35 \end{cases}$$

$$\mu_{middle}^{A}(x_1) = \begin{cases} \frac{x_1-30.}{10} & 30 \le x_1 \le 40 \\ \frac{50-x_1}{10} & 40 \le x_1 \le 50 \end{cases}$$

$$\mu_{old}^{A}(x_1) = \begin{cases} \frac{x_1-45}{10} & 45 \le x_1 \le 55 \\ 1 & 55 \le x_1 \le 60 \\ \frac{70-x_1}{10} & 60 \le x_1 \le 70 \end{cases}$$

$$\mu_{low}^{ICH}(x_2) = \begin{cases} \frac{x_2}{10} & 0 \le x_2 \le 10 \\ 1 & 10 \le x_2 \le 20 \\ \frac{30-x_2}{10} & 20 \le x_2 \le 30 \end{cases}$$

$$\mu_{moderate}^{ICH}(x_2) = \begin{cases} \frac{x_2-20.}{10} & 20 \le x_2 \le 30 \\ \frac{40-x_2}{10} & 30 \le x_2 \le 40 \end{cases}$$

$$\mu_{high}^{ICH}(x_2) = \begin{cases} \frac{x_2-35}{10} & 35 \le x_2 \le 45 \\ 1 & 45 \le x_2 \le 50 \\ \frac{60-x_2}{10} & 50 \le x_2 \le 60 \end{cases}$$

$$\mu_{low}^{HI}(x_3) = \begin{cases} \frac{x_3.}{20} & 0 \le x_3 \le 20 \\ \frac{40-x_3}{20} & 20 \le x_3 \le 40 \end{cases}$$

$$\mu_{medium}^{HI}(x_3) = \begin{cases} \frac{x_3-20}{20} & 20 \le x_3 \le 40 \\ 1 & 40 \le x_3 \le 60 \\ \frac{80-x_3}{20} & 60 \le x_3 \le 80 \end{cases}$$

$$\mu_{high}^{HI}(x_3) = \begin{cases} \frac{x_3-60.}{20} & 60 \le x_3 \le 80 \\ \frac{100-x_3}{20} & 80 \le x_3 \le 100 \end{cases}$$

$$\mu_{poor}^{CS}(x_4) = \begin{cases} \frac{x_4-300}{100} & 300 \le x_4 \le 400 \\ 1 & 400 \le x_4 \le 500 \\ \frac{600-x_4}{100} & 500 \le x_4 \le 600 \end{cases}$$

$$\mu_{average}^{CS}(x_4) = \begin{cases} \frac{x_4-500.}{100} & 500 \le x_4 \le 600 \\ \frac{700-x_4}{100} & 600 \le x_4 \le 700 \end{cases}$$

$$\mu_{excellent}^{CS}(x_4) = \begin{cases} \frac{x_4-650}{100} & 650 \le x_4 \le 750 \\ 1 & 750 \le x_4 \le 800 \\ \frac{900-x_4}{100} & 800 \le x_4 \le 900 \end{cases}$$

$$\mu_{low}^{HIP}(x_5) = \begin{cases} \frac{x_5-1000}{300} & 1100 \le x_5 \le 1400 \\ 1 & 1400 \le x_5 \le 1700 \\ \frac{2500-x_5}{300} & 1700 \le x_5 \le 2000 \end{cases} \quad \mu_{medium}^{HIP}(x_5) = \begin{cases} \frac{x_5-1800}{400} & 1800 \le x_5 \le 2200 \\ \frac{2600-x_5}{400} & 2200 \le x_5 \le 2600 \end{cases}$$

$$\mu_{high}^{HIP}(x_5) = \begin{cases} \frac{x_5-2300}{200} & 2300 \le x_5 \le 2500 \\ 1 & 2500 \le x_5 \le 3000 \\ \frac{3200-x_5}{200} & 3000 \le x_5 \le 3200 \end{cases}$$

Table 1: Further from expert knowledge in insurance eighty one inference rules are to be constructed.

Rules	Age	Insurance Claim History	Health issue	Credit Score	Health Insurance Premium
1	Young	Low	Low	Poor	Low
2	Young	Low	Low	Average	Low
3	Young	Low	Low	Excellent	Low
4	Young	Low	Medium	Poor	Medium
5	Young	Low	Medium	Average	Low
6	Young	Low	Medium	Excellent	Low
7	Young	Low	High	Poor	Medium
8	Young	Low	High	Average	Medium
9	Young	Low	High	Excellent	Low
10	Young	Moderate	Low	Poor	Medium
11	Young	Moderate	Low	Average	Low
12	Young	Moderate	Low	Excellent	Low
13	Young	Moderate	Medium	Poor	Medium
14	Young	Moderate	Medium	Average	Medium
15	Young	Moderate	Medium	Excellent	Low
16	Young	Moderate	High	Poor	High
17	Young	Moderate	High	Average	Medium
18	Young	Moderate	High	Excellent	Medium
19	Young	High	Low	Poor	Medium
20	Young	High	Low	Average	Medium
21	Young	High	Low	Excellent	Low
22	Young	High	Medium	Poor	High
23	Young	High	Medium	Average	Medium
24	Young	High	Medium	Excellent	Medium
25	Young	High	High	Poor	High
26	Young	High	High	Average	High
27	Young	High	High	Excellent	Medium
28	Middle	Low	Low	Poor	Medium
29	Middle	Low	Low	Average	Low
30	Middle	Low	Low	Excellent	Low
31	Middle	Low	Medium	Poor	Medium
32	Middle	Low	Medium	Average	Medium
33	Middle	Low	Medium	Excellent	Low
34	Middle	Low	High	Poor	High
35	Middle	Low	High	Average	Medium
36	Middle	Low	High	Excellent	Medium
37	Middle	Moderate	Low	Poor	Low
38	Middle	Moderate	Low	Average	Medium
39	Middle	Moderate	Low	Excellent	Low
40	Middle	Moderate	Medium	Poor	High
41	Middle	Moderate	Medium	Average	Medium
42	Middle	Moderate	Medium	Excellent	Medium

43	Middle	Moderate	High	Poor	High
44	Middle	Moderate	High	Average	High
45	Middle	Moderate	High	Excellent	Medium
46	Middle	High	Low	Poor	High
47	Middle	High	Low	Average	Medium
48	Middle	High	Low	Excellent	Medium
49	Middle	High	Medium	Poor	High
50	Middle	High	Medium	Average	High
51	Middle	High	Medium	Excellent	Medium
52	Middle	High	High	Poor	High
53	Middle	High	High	Average	High
54	Middle	High	High	Excellent	High
55	Old	Low	Low	Poor	Medium
56	Old	Low	Low	Average	Medium
57	Old	Low	Low	Excellent	Low
58	Old	Low	Medium	Poor	High
59	Old	Low	Medium	Average	Medium
60	Old	Low	Medium	Excellent	Medium
61	Old	Low	High	Poor	High
62	Old	Low	High	Average	High
63	Old	Low	High	Excellent	High
64	Old	Moderate	Low	Poor	High
65	Old	Moderate	Low	Average	Medium
66	Old	Moderate	Low	Excellent	Medium
67	Old	Moderate	Medium	Poor	High
68	Old	Moderate	Medium	Average	High
69	Old	Moderate	Medium	Excellent	Medium
70	Old	Moderate	High	Poor	High
71	Old	Moderate	High	Average	High
72	Old	Moderate	High	Excellent	High
73	Old	High	Low	Poor	High
74	Old	High	Low	Average	High
75	Old	High	Low	Excellent	Medium
76	Old	High	Medium	Poor	High
77	Old	High	Medium	Average	High
78	Old	High	Medium	Excellent	High
79	Old	High	High	Poor	High
80	Old	High	High	Average	High
81	Old	High	High	Excellent	High

4. Method for defuzzification:

We have employed the mean of maxima method (MOM) for defuzzification

Let us consider of a prospective policyholder: $x_1 = 34, x_2 = 32, x_3 = 85, x_4 = 510$

The membership function used to determine the fuzzy values that correspond to them.

$\mu^{A}_{young}(34) = \frac{35-34}{5} = \frac{1}{5}$ $\mu^{A}_{middle}(34) = \frac{34-30.}{10} = \frac{4}{10}$

$\mu^{ICH}_{moderate}(32) = \frac{40-32}{10} = \frac{8}{10}$

$\mu^{HI}_{high}(85) = \frac{100-85}{20} = \frac{15}{20}$

$\mu^{CS}_{poor}(510) = \frac{600-510}{100} = \frac{90}{100} = \frac{9}{10}$ $\mu^{CS}_{average}(510) = \frac{510-500.}{100} = \frac{10}{100} = \frac{1}{10}$

$min\left\{\mu^{A}_{young}, \mu^{ICH}_{moderate}, \mu^{HI}_{high}, \mu^{CS}_{poor}\right\} = min\left\{\frac{1}{5}, \frac{8}{10}, \frac{15}{20}, \frac{9}{10}\right\} = \frac{1}{5}$ (Strength of Rule 16)

$min\left\{\mu^{A}_{young}, \mu^{ICH}_{moderate}, \mu^{HI}_{high}, \mu^{CS}_{average}\right\} = min\left\{\frac{1}{5}, \frac{8}{10}, \frac{15}{20}, \frac{1}{10}\right\} = \frac{1}{10}$ (Strength of Rule 17)

$min\left\{\mu^{A}_{middle}, \mu^{ICH}_{moderate}, \mu^{HI}_{high}, \mu^{CS}_{poor}\right\} = min\left\{\frac{4}{10}, \frac{8}{10}, \frac{15}{20}, \frac{9}{10}\right\} = \frac{4}{10}$ (Strength of Rule 43)

$min\left\{\mu^{A}_{middle}, \mu^{ICH}_{moderate}, \mu^{HI}_{high}, \mu^{CS}_{average}\right\} = min\left\{\frac{4}{10}, \frac{8}{10}, \frac{15}{20}, \frac{1}{10}\right\} = \frac{1}{10}$ (Strength of Rule 44)

$Maximum\ strength = max\left\{\frac{1}{5}, \frac{1}{10}, \frac{4}{10}, \frac{1}{10}\right\} = \frac{4}{10}$

Rule (43) has the maximum strength and its outputs is high.

$\frac{x_5-2300}{200} = \frac{4}{10}$

$x_5 = 2380$

$\frac{3200-x_5}{200} = \frac{4}{10}$

$x_5 = 3280$

The defuzzification of the data into crisp output is accomplished by combing the results of the inference process. Now using this method our applicant would now pay.

$x_5{}^* = \frac{2380+3280}{2} = \frac{5660}{2} = 2830$

Table 2: Estimated values of health insurance premium using FLS

Rules	Age	Insurance Claim History	Health issue	Credit Score	Health Insurance Premium
1	44	30	50	575	2160
2	28	19	13	439	1650
3	30.9	34.3	49.7	586	1670
4	32.6	23.4	24.7	421	2050
5	64.9	51.5	85.8	751	2750
6	44.4	37.6	51.4	784	2530
7	28.8	18.7	63.6	674	1730
8	37.8	37.3	26.4	445	2110
9	54.5	21.4	63.6	687	2140
10	43.3	24.7	41.4	436	2700
11	27.7	7.46	10.3	341	1630
12	30.9	31.7	66.9	512	2320
13	19	3.48	5.83	448	1610
14	34	26	85	510	2750
15	38.1	22.4	40.3	500	2410

5. 3D surface plot of the variables: A Fuzzy-Based Framework for Individualized Health Insurance Premium Calculations' 3D surface plot helps clarify the model's output variable, premium costs. Personal health insurance premiums are calculated by taking a number of factors into account, including the policyholder's age, insurance claim history, health issues, and credit score. This interactive tool makes it easy to see how these factors relate to one another. Here, the three-dimensional surface plot provides a live illustration of the effect of changing input variables on the output variable. This provides stakeholders, like as policyholders and insurers, with thorough figures of the elements that impact personalized premium estimates.

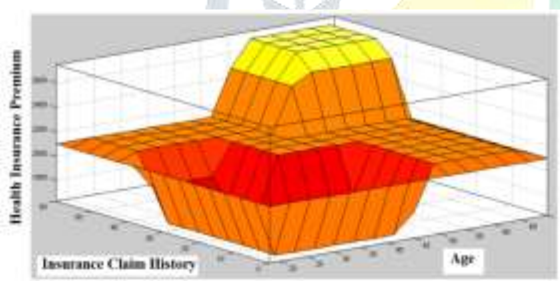

Figure 6: 3D surface plot of health insurance premium for different values of age and insurance claim history

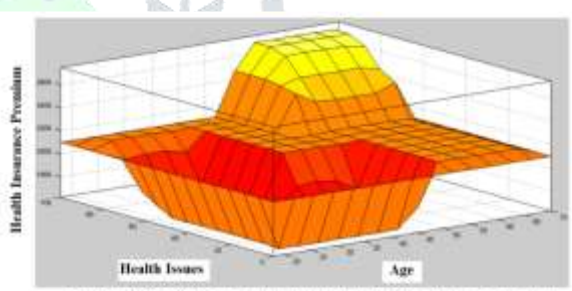

Figure 7: 3D surface plot of health insurance premium for different values of age and health issues

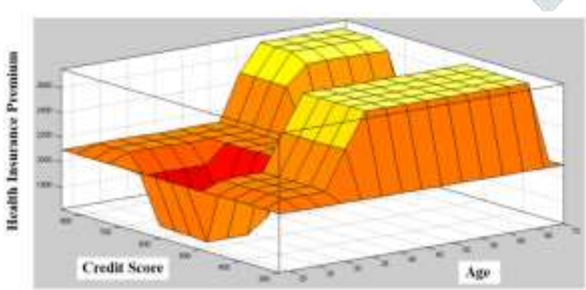

Figure 8: 3D surface plot of health insurance premium for different values of age and credit score

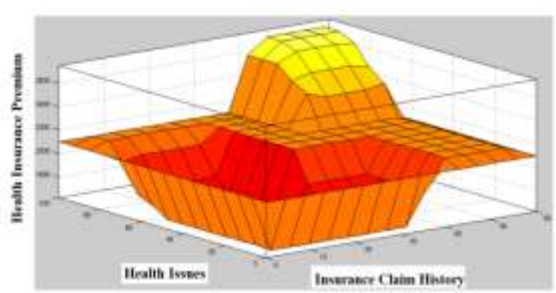

Figure 9: 3D surface plot of health insurance premium for different values of insurance claim history and health issues

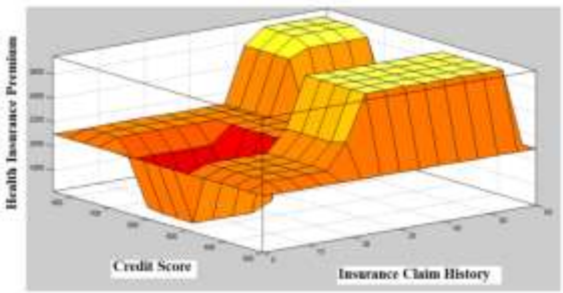

Figure 10: 3D surface plot of health insurance premium for different values of insurance claim history and credit score

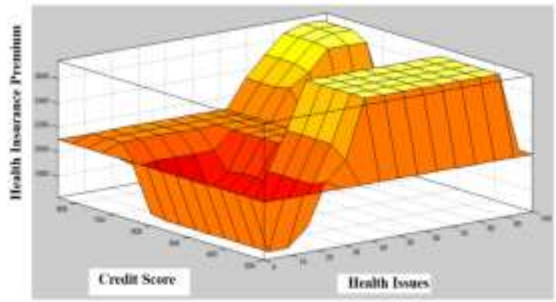

Figure 11: 3D surface plot of health insurance premium for different values of health issues and credit score

One can see the correlation between the policyholder's age, insurance claim history, and premiums in a three-dimensional surface plot in figure (6). The plot shows the computed health insurance premium as a function of the policyholder's age and claim history, with each point on the plot representing a combination of these two variables. One can get a vague idea of the relationship between age, insurance claim history, and health insurance premiums by looking at the surface form. The preliminary data points to either an upward trend in insurance premiums with age or a general trend towards higher rates for policyholders with a history of claim filings.

Looking at the surface shape in figure (7), which shows the development of health insurance premiums over time, helps to understand the link between age and health problems. Our research indicates that premiums increase in tandem with the ageing population and the frequency of health issues. We can use the plot to visually evaluate the risk linked to various age and health condition combinations. Greater concentrations of the elderly, people with serious health issues, or both may explain why certain regions have higher rates than others.

On the figure (8), there are several spots called peaks that show where the premium is significantly higher than average. These results show that certain age groups and combinations of credit scores are more likely to see increases in insurance premiums. Compared to other areas, insurance premiums in valleys are significantly lower. Because it makes use of fuzzy logic, the system can deal with input variables that aren't perfectly known or precise. Because of the nebulous character of age groups and credit scores, it's possible that the plot will show less abrupt changes between them.

Alterations made in response to changes in health conditions and insurance claim records cause fluctuations in health insurance prices, as shown in figure (9). Insurance premiums are inversely proportional to the incidence of health problems and claims. This chart can help insurers understand the various variables that go into determining individual premiums. On top of that, policyholders can learn how their medical history and current health status impact their insurance premiums.

Variations in health insurance premiums according to claim history and credit score are seen in figure (10). A decrease in credit score is positively correlated with an increase in insurance claims, which in turn leads to increased insurance premiums. The data needed to visually assess the risk associated with various combinations of credit scores and insurance claim histories is provided by the graphic. A higher risk level may be indicated by higher premiums in some areas, which could be a result of a history of several claims, poor credit, or both.

Figure (11) shows how health insurance rates vary with different health conditions and credit ratings, and how these factors impact the rates. An increase in health problems and a decline in credit score are the two most common causes of rate increases. The surface peaks show regions with very high insurance premiums, suggesting that people with certain health conditions and credit ratings are more likely to pay those rates. Compared to other areas, insurance premiums in valleys are significantly lower.

6. Concluding Remarks: The insurance business is experiencing tremendous changes, leading to an increased need for tailored services that is more crucial than ever. The research we conducted has resulted in the creation and application of a Fuzzy-Based Framework, which has provided a novel approach to calculating insurance premiums. As we approach the end of our analysis, we will now evaluate the importance of our contributions and propose potential directions for further research and implementation.

The primary advantage of our methodology is its proficient utilization of fuzzy logic to handle the inherent complexity in insurance risk assessment. The efficacy of our approach resides in its capacity to precisely depict the intricate and puzzling attributes of real-world data by employing trapezoidal and triangular membership functions for essential input variables. The factors consist of age, claim history, annual income, and credit score. The use of membership functions allows for a more precise depiction of individual risk profiles, hence simplifying the calculation of premiums that are both accurate and customized for each person.

Our system, which utilizes fuzzy logic, is a significant step towards the future of insurance services as it enables the determination of personalized insurance rates. By utilizing the adaptability and flexibility of fuzzy logic, we can actively contribute to the continuous development of the industry, which highlights the highest significance of accuracy, neutrality, and customization. As we go forward to the next stage of our journey, we are excitedly looking forward to the additional development, collaborations, and practical uses that will increase the importance of fuzzy logic in influencing the future of customized insurance services.

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