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Multicriteria Recommendation System for Life Insurance Policies using Grey Relational Analysis Method

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ABSTRACT:
Background/Objectives: This paper suggests a recommendation system for life insurances policies. Life Insurances policies are useful for anyone who wants to protect their families, properties/assets and themselves form financial problems. Insurances policies also helps to cover expenses during medical emergencies. This as made a remarkable increase in the number of insurance products in the market which in turn increase the competition in the insurance sector of India.
Methods: Grey Relation Analysis (GRA) is used to find the suitable plans over different available policies.
Results: The aim of this recommendation system is to suggest most suitable insurance policy to the customers. Our recommender system filters the users demographic specifications to match the constraints of policies according to the information given by user using grey relational analysis.
KEYWORDS: Multicriteria recommendation system, grey relational analysis, life insurance policies.

I. INTRODUCTION

It is vital to have a lot of information in order to make effective decisions. However, there are countless cases that indicate that having too much information is just as dangerous as having too little. Information overload is the result of insufficient information.Recommender System has been introduced to solve problems.It's a popular and practical notion. In today's digital era. It is a system for filtering information.that suggests the most relevant products and services.

The Recommender System has been widely employed in the entertainment industry for products and services such as online games, restaurants, and music, books, and movies entirely based on user feedback. Additional applications are Personalized Business-to-Business, E-Services, Mobile Apps With Criticism Recommendation, Fashion Recommender With Intelligence System, Recommendation for an Academic Paper. These Users keep trying new items since they are routine products. products on a regular basis; It is only a minor concern if they fail to please certain of their users.and has little impact on people daily lives.

Consider an item that performs a vital purpose and is meant to help users in the case of a future emergency, but can only be obtained by a selected few in their lifetime and each person has their own preferences for the items. That is impossible to generalise. Appropriate suggestions,Users' contextual opinions on such products are required. As traditional recommender systems rely solely on it.They are based on parallels between products and users and do not work well with the afore mentioned products. Life insurance is an example of this type of product. Liberalization of the Indian insurance market has produced a number of companies.Increasing competition among insurance providers has resulted in a vast array of insurance products. Insurance policies have a lot of features and a lot of vocabulary. Customers also have difficulty understanding the terms and conditions of insurance products. As a result, a recommendation system that hides complexities and proposes the best policies to its users has been needed for a long time.This study offers a Utility-Based Multi Criteria Recommender System that provides consumers with the best insurance coverage based on their preferences. User's choice is elicited by the use of Intuitionistic Fuzzy Sets (IFS)and Grey Relational Analysis is used to measure the policy's usefulness to the user. The system predicts policies that are likely to be implemented according to users' requirements. The proposed mechanism makes user to easily understand the Insurance that as a lot of complicated words, conditions, and computations. It also makes selecting life insurance policy straightforward.

II. PRELIMINARIES

2.1 RECOMMENDATION SYSTEM

Recommendation system has been proved significant method of solving the information overload problem. It saves precioustime of consumers while searching for products and services of their interest. It is the criteria of ‘personalized’ and ‘interesting and useful’ that makes distinction between recommender system and information retrieval systems. Recommendation technique is the core of the recommendation system. Main components of the recommendation system are background data, input data and the algorithm. Background data refers to information which is required by the system before the recommendation is made. Input data refers to information which is provided by users in order to generate a recommendation. The algorithm is a process that combines background data and input data for arriving at suggestion . In his paper Burke categorized Recommender system as:

a) Content-based recommender system: A content-based recommender system promotes products based on the item's text information. It suggests goods to the user that are comparable to those that were previously preferred. The Pearson's correlation method or a Cosine-based method can be used to calculate the similarity between objects.

b) Collaborative filtering: A collaborative filtering-based recommender system is similar to a content-based recommender system, with the exception that it calculates user similarity rather than item similarity. Users who are similar to the target user are referred to as neighbours. The neighborhood-based collaborative filtering recommendation technique suggests goods to a target user based on what his neighbours are looking for.

c)Demographic: The recommendation system categorises persons or goods based on the user's personal attributes and makes recommendations based on those categorizations.

d) Utility-based: Recommendations are made based on the product's utility to the user; the product with the greatest utility is recommended. Each item's utility is computed for each user, which necessitates the storage of a utility function.

e) Expertise-based: The recommendation is based on domain knowledge, which can be gleaned from a domain expert or a thorough review of the literature. Expert systems and content-based filters can be combined to form a knowledge-based system.

f)Hybrid: It's a mix of two or more recommendation techniques that works to overcome the limits of each algorithm. The majority of recommender systems today employ a hybrid method that combines collaborative filtering, content-based filtering, and other techniques. Hybrid approaches can be implemented in a variety of ways, including making content-based and collaborative-based predictions

The Recommender Systems forecast items that are attractive and relevant to the consumers using a variety of data analysis methodologies. MCRS (Multi Criteria Recommender System) is a Recommender System expansion that uses MCDM methods and techniques from the MCDM discipline. This paper is primarily concerned with MCRS.

2.2 RECOMMENDATION AS MULTI CRITERIADECISION MAKING MODEL

Multi Criteria decision Making (MCDM) is a cognitive process that involves modelling and solving decision issues with numerous criteria or qualities. When several competing criteria are present, the goal of MCDM is to assist a decision maker in selecting the optimal possibilities. Traditional recommender systems employ data mining techniques for collaborative filtering and single-criteria content-based recommendations (often ratings). Multi Criteria Recommender Systems are systems that use many criteria to provide recommendation (MCRS).

One of the standard MCDM approaches can be used to add numerous criteria into a core recommendation problem. One of the early proponents of MCDM, presented an approach for general modelling of decision-making situations. When examining a decision-making problem, Roy's methodology contains four steps:

a)Defining the decision object: The decision object is an alternative that must be chosen from among all candidate alternatives. Alternatives might be items or a path of action, and a decision must be taken between them.

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b)Using a set of criteria to define a consistent family of criteria: The performance of alternatives is assessed. This stage entails identifying all criteria that influence the decision's goal. These should be comprehensive and non-redundant, and should cover all of the factors that influence the decision.

c) Global Preference Model: In this stage, an aggregator function is created, which determines the decision maker's global preference for each item by synthesising partial preferences based on each criteria.

d) Decision support process: This stage entails the creation and implementation of procedures or software systems to aid choice makers in reaching a final decision (based on the outcomes of previous steps) for a given MCDM challenge.

III. PROPOSEDRECOMMENDER SYSTEM

The suggestion is a multi-criteria decision issue; the recommendations are based on product performance against specific criteria and user preferences. The system's goal is to recommend the most promising policies to users.

3.1 SYSTEM FRAMEWORK

The suggested system is divided into three stages. Before the recommendation process begins, a knowledge required by the system. The second phase collects specific inputs from the user, and the third step is the recommendation phase, which generates inferences based on a combination of background data and user inputs. Fig 1 depicts the operation of Multi criteria recommendation system model.

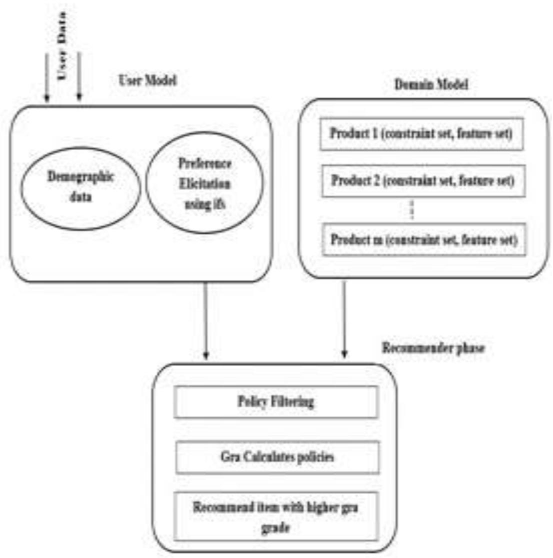

Fig 1: System Framework

3.1.1 DOMAIN MODELING

During this phase, information about each product in the Policy set is supplied into the system; a policy has two subsets: a set of constraints that a customer must meet, which defines the target customers, and a collection of features that explains the benefits that the product provides to those customers.

3.1.1.1 CONSTRAINTS SET

In the research, author discovered four intrinsic constraints of an insurance policy that must be matched with the user's demographic specifications:

a) Age of Admission:The customer's age must be between the minimum and maximum entrance age. It has an impact on the premium amount; the younger you are, the lower the premium.

b) Sum-Assured: The sum-assured is the minimum amount that an insurance company must pay in the event of the policyholder's death. Every insurance has a minimum and maximum sum assured, resulting in a range from which consumers can pick.The majority of policies have a "No Limit" maximum sum-assured clause. It also affects the amount of premium; the higher the sum-assured, the higher the premium.

c) Duration: A policy's duration refers to how long it is valid.Every insurance has a minimum and maximum term, creating a spectrum from which clients can select one. It also affects the amount of premium paid; the longer the period, the lower the premium.

d) Maturity:(Age, Experience) The maturity-age of a client is the age at which the policy becomes "matured."

Although most polices have a maximum maturity age, only a handful (typically geared for children) have a minimum maturity age. The total age and term of the consumer must be less than or equal to the maturity age.

The suggested recommendation system compares these restrictions to the demographic information provided by the user and filters only those rules that satisfy the constraints.

3.1.1.2 FEATURES SET

Dutta identified nine critical life insurance policy parameters:

1. Affordable premium
2. Payment structure flexibility
3. Insurance plan tax advantages
4. Death-related benefits
5. Survival advantages
6. Outstanding customer service:
• Payment over the internet,
• Renegotiation of the term/amount insured
7.Bonus
8. Add-ons and Special Plans:

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• Group schemes.
• Loan against policy
9. Riders are available, allowing insurance plans to be customised:
• Benefits for accidents and disabilities;
• Benefits for critical illnesses.
The suggested recommendation system uses these qualities as insurance policy evaluation criteria, calculating the utility of each element to determine overall usefulness.

IV. POLICY FILTERING

Before completing utility calculations, the proposed system filters policies whose restrictions are satisfied by user information. As previously said, a life insurance policy has some intrinsic qualities or limits, which they have listed. These are the limitations:

- Maturity Age
- Entry Age
- Duration
- Sum Assured

In order to create a good recommender system, there must be little user intervention. The proposedrecommendation system receives age and income as input data for correlating entry-age and maturity-age; because age and income are user-specific facts that cannot be chosen explicitly (a 17-year-old does not have the option to choose his age and buy a policy with a minimum entry age of 18), the system must obtain this information from the user. Term and sum-assured, on the other hand, are adjustable attributes that the user selects from a scale (min, max), and so the most appropriate values can be chosen by the user or recommended by the system.

A person is not permitted to purchase life insurance plans in excess of the IRDA's set maximum. The total of all client policies should be less than or equivalent to this limit. By evaluating a customer's age, income, and risk preferences, the underwriting process determines to what extent a customer can acquire a policy. The designed methodology assumes that system users have no prior policies. Because most policies have "No Limit" for maximum sum-assured, the system determines the maximum amount of insurance that consumers can purchase and uses that as the maximum sum-assured to produce a range (min sum-assured, max sum-assured).

Estimating Grey relation grade of policies to the user using GRA

Step 1: For a multicriteria recommendation system ,if there are **a**policies (alternatives) and **b**features (attributes) ,the $\mathbf{x^{th}}$ value can be written as $\mathbf{J_x} = (\mathbf{j_{x1}}, \mathbf{j_{x2}} \ldots \mathbf{j_{xn}})$ where $\mathbf{j_{x1}}$, is the performance value of **x** over attribute **y**. The value of$\mathbf{J_x}$ can be converted into comparability expression $\mathbf{I_x} = (\mathbf{i_{x1}}, \mathbf{i_{x2}} \ldots \mathbf{i_{xn}})$. By using Eq.(1),

$$i_{xy} = \frac{j_{xy} - \min\{j_{xy}, x=1,2,\ldots a\}}{\max\{j_{xy}, i=1,2,\ldots a\} - \min\{j_{xy}, x=1,2,\ldots a\}} \quad \ldots (eq\text{-}1)$$

Step 2 : All performance scores will then be ranging from [0, 1] after the grey relation generation using Eq. (1). If the value of an attribute **y** of alternative **x** is equal to $\mathbf{i_{xy}}$or nearer to 1 than the value of any other alternative, it means that alternative **x** performance is the best for the attribute **y**. However, because this type of alternative is rarely available, a reference sequence $\mathbf{i_0}$ must be described as $(\mathbf{i_{01}}, \mathbf{i_{02}}, \ldots \mathbf{i_{0b}}) = (\mathbf{1,1 \ldots,1})$.The reference sequence is a hypothetical ideal alternative that is used to assess the performance of other alternatives.

Step 3 : Grey relationship coefficients are computed in this stage. It establishes the distance between ixy and i0y. The higher the grey relationship coefficient, the closer ixy and i0y are. Eq. (2) may be used to compute the grey relationship coefficient.

$$Y_{xy} = Y(i_{oy}, i_{xy}) = \frac{\Delta min + \flat \Delta max}{\Delta_{ij} + \flat \Delta max} \quad \ldots (eq\text{-}2)$$

$\mathbf{Y_{xy}}$ is the grey relational coefficient between $\mathbf{i_{0y}}$ and $\mathbf{i_{xy}}$ in Eq. (2). Δ_{xy} is the distance between $\mathbf{i_{0y}}$ and $\mathbf{i_{xy}}$, Δ_{max} and Δ_{min} is the lowest and greatest value of Δ_{xy} . **þ** is a user-controlled separating coefficient, **þ € [0,1].** The goal of the differentiating coefficient is to broaden or narrow the range of grey relationship coefficients.

Step 4 : This is the final step where grey relational grade is evaluated using equation 3,

$$\xi_x = \sum_{y=1}^{b} w_y \gamma_{xy}, \text{ for } x = 1, 2, \ldots\ldots, a. \quad \ldots (eq\text{-}3)$$

Where ξ_x is the policy's grey relational grade, which represents the policy's total score. $\mathbf{Y_{xy}}$ is the grey relational coefficient of $\mathbf{x^{th}}$ policy over $\mathbf{j^{th}}$ feature, $\mathbf{W_y}$ reflects the weight of the feature.

V. GRA BASED MULTICRITERIA RECOMMENDATION SYSYTEM

The procedure for the GRA Based Multi Criteria Recommendation System is described in this section:

Step 1: Obtain the user's age, income, duration, and sum-assured.

Step 2: The user specifies his or her preferences for various insurance policy characteristics.

Step 3: Assess the significance of the criteria to the user.

Step 4: Proposed model filter policies that are compatible with the user's profile.

Step 5: Each policy's performance over each feature is assessed.

Step 6: Evaluate grey relational co-efficient for every policy over the criteria provided by the user.

Step 7: Determine the over all result by using grey relation grade of every policy.

Step 8: Recommend the policies with higher grey relation grade to the users.

VI. CONCLUSION

Author proposed a new GRA-based recommendation system to aid in the decision-making process when it comes to insurance coverage. Unlike existing recommender systems, which are primarily concerned with relationships between products and consumers, the suggested system bases its recommendations on the user's contextual requirements. The suggested system screens insurance policies that match the user's demographic information, determines them based on the user's preferences, and recommends policies to the users with the highest grey relation grade. Insurance is a critical need in today's unpredictable world, but deciphering the features, terms, and conditions of each policy is a time-consuming procedure that is always influenced by the prejudices of insurance agents.

In the literature, author compared the suggested system to other existing recommendation system and decision support system for insurance. Other systems rely on fuzzy logic and data mining to recommend policies or policy parts, but they don't take into account the user's preferences. Because insurance is a context-based product, even the same customer can purchase different plans in different scenarios, the user's preferences play a big role in the accuracy of recommendations. The recommendation system uses user inputs to elicit user preferences for evaluating criteria, resulting in more personalised recommendations.

In future study, the author will focus on making the user interest elicitation process easier. The intend to create an efficient algorithm that needs less user intervention while maintaining all of the benefits of the current system. The future research will also focus on developing a demographic-based insurance recommendation system. The intend to design a recommendation system system that gets demographic user information and their families and forecasts their present and future needs, as insurance is a product acquired to support family in the event of a contingency. The system will also suggest a set of rules to achieve these goals.

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