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DEVELOPMENT OF AN INSURANCE SCORING SYSTEM BASED ON THE PAIRWISE COMPARISON METHOD

The article presents the process of developing an insurance scoring model based on the pairwise comparison method. Within the framework of the research, the weights of the main indicators, such as payment history, credit score, claims history, etc., were determined based on expert assessments.

This research contributes to the introduction of a scoring system in the Armenian insurance market, based on international best practices and local conditions.

The use of a scoring system will allow insurance companies to more effectively classify customers by risk level, which will allow them to better assess the potential volume of liabilities and ensure more predictable cash flows. As a result, companies can effectively allocate their investment assets, reduce the risk of large losses and improve overall financial stability. Thus, the introduction of insurance scoring will not only help reduce losses and justify tariff policy but will also become an important tool for increasing the efficiency of asset management for the long-term stability of insurance companies.

Keywords: *insurance score, risk management, analytical hierarchy process, pairwise comparison, indicator normalization, financial discipline, tariff, credit score*

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INTRODUCTION. Insurance scoring is an effective tool for assessing customer risk in the financial and insurance sectors, based on data-driven analysis and modeling methods. It allows insurance companies to predict customer behavior, assess the likelihood of their claims and the level of financial responsibility. The use of the system allows not only to fairly classify customers by risk level, but also to develop personalized customer service models, which significantly increases the efficiency of the insurance business. As a result of assessing customer risk, insurance companies can develop more optimal capital allocation strategies, predicting the probability of loss and the level of stability of the investment portfolio, ensuring more stable and strategic management mechanisms. Scoring data can be used to assess risks in the insurance asset portfolio, which allows for more effective allocation of the company's capital, ensuring investment stability and long-term growth. The score is especially important for assessing customer solvency. It reduces the risks associated with debt management by predicting delays or non-payments. This research aims to propose an insurance scoring model that can be implemented in any insurance system, which will allow insurance companies to more accurately assess the riskiness of customers, conduct an effective pricing policy, improve asset management strategies and, why not, optimize investment decisions. The article will discuss international best practices, methodologies for applying insurance scoring, and data usage opportunities, with an emphasis on the conditions of the Armenian market.

LITERATURE REVIEW. The international scientific literature on insurance scoring presents various models and methodologies that are used to assess customer risk, optimize pricing policies, and increase the financial stability of insurance companies. This topic has been widely studied in different countries, especially in developed insurance markets, where scoring systems are based on big data analysis and machine learning methods.

The use of insurance scoring systems has been widespread in the insurance markets of the United States and Europe since the 1990s. In the Asian market, this system is still relatively new, although it has already been introduced in a number of countries in the region, especially in the field of automobile insurance (Lawrence, 1996).

However, numerous studies on insurance scoring systems have been conducted since the 1980s. Cootes (1984), Brockman and Wright (1992), Miller and Smith (2003), Anderson et al. (2004), Wu and Lacker (2004), Wu and Guscha (2004), and Wojtek and Kochenda (2006) have proposed various models that suggest various mechanisms that could influence the development of the scoring system, and many researchers have already begun to analyze the degree of influence of credit scores on the occurrence of insurance accidents. Finally, in 2007, a US Federal Trade Commission analysis shows that insurance scores based on credit history are effective in predicting insurance risk, especially in the case of automobile insurance. The use of scores can make insurance premiums more closely aligned with insurance risk, with higher-risk consumers paying higher premiums on average and lower-risk consumers paying lower premiums. However, it is not yet clear why credit scores predict insurance risk (Federal Trade Commission, 2007).

Researchers Brockett and Golden also examined the applicability of credit scores to predict insurance losses based on biological, psychological, and behavioral factors. The authors showed that psychological characteristics often influence the volume of insured events. The results of the study indicate that credit scores provide additional information for assessing insurance risks that is missing from traditional actuarial variables (e.g., age, driving history). Thus, credit scoring can serve as an additional predictive tool in the insurance loss assessment and risk management processes (Brockett et al., 2007).

Researchers Ismail and Jemain (2008) studied methods for constructing an insurance scoring system, proposing regression models. The authors emphasize that the scoring system can help insurance companies distinguish between high and low risk or "good" and "bad" policyholders/insured persons, which allows them to predict the profitability of insurance contracts (Ismail et al., 2008).

Researchers Golden and co-authors conducted an empirical analysis on behalf of the insurance industry and state legislatures, examining data from more than 175,000 insured individuals. The results of the analysis showed that credit scores are significantly associated with insurance losses across various types of insurance and add new information to the assessment of insurance risk that is not captured by traditional indicators such as age, gender, or driving history. The authors suggest that new, non-traditional indicators, including social media data and information derived from technological advances, should be included in the prediction of insurance scores (Golden et al., 2016).

Matiyazova, a researcher at the Tashkent Institute of Finance, studied the need to introduce an insurance scoring system and noted that insurance companies in Uzbekistan currently do not use such a mechanism. The author emphasizes that the lack of a scoring system is due to the limited availability of historical statistical data. The introduction of scoring can improve the process of developing insurance contracts, reduce insurance fraud cases, and ensure optimal pricing policy (Matiyazova, 2022).

Researchers Stiff and Bell found that over the past 15 years or so, the personal, property, and liability insurance industry has been studying and using individual credit history in various ways to build pricing models and underwrite policies. Credit scores are just one of hundreds of factors that insurance companies consider. Today, most insurance companies consider at least 30 or more factors, compared to a handful that were previously considered, unfortunately, unpublished (Stiff et al., 2019).

By analyzing international experience, we can state that:

➢ Although most researchers in international practice have relied on credit history, insurance companies' decisions are not and cannot be based only on credit history, many other data are used for justification, the data include both factors directly related to insurance risk (for example, in the case of car insurance, driving history, car type, age, gender, geographical location), as well as data related to financial behavior. Different insurance companies use different approaches, developing their own scoring models. Some components of these models, sometimes completely, are kept secret, when the legislation allows it. The reason is that these assessments are of great importance in ensuring competitiveness in the insurance market.

➢ Although some components of the models, sometimes completely, are kept secret, when the legislation allows it. The reason is that these assessments are of great importance for ensuring competitiveness in the insurance market, which is widely studied and has standardized calculation models, insurance scoring methodologies are still in the development stage and are applied mainly in closed systems, which have limited access to academic and practical researchers. As a result, insurance companies mainly use their own methodologies without their academic or theoretical justification.

Despite the abundance of literature and research on scoring, some components and mechanisms of calculation are often kept secret, sometimes completely. By filling this gap, this study will be the first step that can serve as a basis for the development and application of insurance scoring systems in Armenia, contributing to market development and more effective risk management.

RESEARCH METHODOLOGY. The research used quantitative methods, an approach to determining weights based on expert assessments, and mathematical modeling. The expert assessment method was used to collect data. Experts were offered to evaluate using the pairwise comparison method, which is one of the multidisciplinary decision-making methods The pairwise comparison approach was selected because it allows the aggregation of expert judgments in cases of limited data availability, ensuring consistency and transparency.. In this case, the pairwise comparison method was used to determine the weights of various factors for the insurance score. 10 experts participated in the survey, who were selected according to the following criteria:

- At least 5 years of work experience in the insurance sector
- Specialization in actuarial calculations, financial analysis, or insurance risk management
- Participation in previously conducted analyses or expert assessments

The relatively small sample size is explained by the limited number of professionals in the Armenian insurance market who possess specialized knowledge in actuarial science, risk modeling, and underwriting. Engaging qualified experts proved challenging due to the niche nature of the field and their limited availability

The experts were offered a pairwise comparison method to assess the relative importance of six main indicators, which made it possible to form the best structure of the scoring system.

We present these six indicators in two main groups:

1. Financial discipline indicators, which reflect the financial responsibility and solvency of the client.

- Payment history (A)
- Credit score (B)

2. Risk behavior indicators, which characterize the client's insurance behavior and riskiness.

- Fraud history (C)
- Claims history (quantity) (D)
- Claims history (amount) (E)
- Insurance history (terminated contracts) (F)

This grouping allows insurance companies to take a comprehensive approach to assessing the riskiness of clients, taking into account both their financial discipline and insurance behavior.

Referring to the indicators, we can say that they were selected taking into account several justifications. First, they reflect the client's financial discipline, insurance history and level of riskiness. Second, they are widely used in the insurance and credit sectors for the purpose of risk assessment and tariff policy formation. Finally, the selection of indicators is based on international experience and the risk modeling requirements of insurance companies, providing a comprehensive analysis of customer reliability and risk.

However, for further research, the model can be expanded to include additional variables such as:

- demographic factors (age, gender, residence region);
- behavioral factors (driving experience, accident history);
- macroeconomic factors (income stability, unemployment rate, regional loss frequency).

Each newly added indicator will be subjected to the same pairwise comparison and weight derivation process, followed by empirical validation using company-level data.

ANALYSIS: According to the *pairwise comparison method*, the 10 selected experts carried out pairwise comparisons between the evaluated objects by assigning scores. The evaluation was conducted based on the following logic:

When the i-th object is compared to the j-th object, the scores are defined as follows:

$$a_{ij} = \begin{cases} 2, & O_i > O_j \ \text{(i − th object is superior to j − th)} \\ 1, & O_i \sim O_j \ \text{(both are equivalent)} \\ 0, & O_j > O_i \ \ (j - th\ object\ is\ \text{osuperior}\ i - th) \end{cases}$$

Additionally

$$a_{ij} = 1, when\ \ i = j{:}\, If\ a_{ij} = 2\ then\ a_{ji} = 0$$

As a result, each expert provided an evaluation matrix, leading to 10 separate tables containing the pairwise comparison results.

As a result, the following 10 tables of evaluation by each expert were formed.

Table 1

Experts' Evaluations (p_1, p_2, p_3…p_{10})

p1	**A**	**B**	**C**	**D**	**E**	**F**	$a_i^{'}$
A	**1**	0	1	1	0	2	5
B	2	**1**	1	2	1	2	9
C	1	1	**1**	1	0	0	4
D	1	0	1	**1**	0	1	4
E	2	1	2	2	**1**	1	9
F	0	0	2	1	1	**1**	5

p2	**A**	**B**	**C**	**D**	**E**	**F**	$a_i^{'}$
A	**1**	1	0	1	0	1	4
B	1	**1**	1	2	1	2	8
C	2	1	**1**	2	1	2	9
D	1	0	0	**1**	0	1	3
E	2	1	1	2	**1**	2	9
F	1	0	0	1	0	**1**	3

p3	**A**	**B**	**C**	**D**	**E**	**F**	$a_i^{'}$
A	**1**	0	1	1	0	1	4
B	2	**1**	1	2	1	1	8
C	1	1	**1**	2	1	2	8
D	1	0	0	**1**	0	1	3
E	2	1	1	2	**1**	2	9
F	1	1	0	1	0	**1**	4

p4	**A**	**B**	**C**	**D**	**E**	**F**	$a_i^{'}$
A	**1**	0	0	1	0	1	3
B	2	**1**	1	2	1	2	9
C	2	1	**1**	2	1	2	9
D	1	0	0	**1**	0	1	3
E	2	1	1	2	**1**	0	7
F	1	0	0	1	2	**1**	5

p5	**A**	**B**	**C**	**D**	**E**	**F**	$a_i^{'}$
A	**1**	0	0	1	1	1	4
B	2	**1**	2	2	1	1	9
C	2	0	**1**	1	1	2	7
D	1	0	1	**1**	0	1	4
E	1	1	1	2	**1**	1	7
F	1	1	0	1	1	**1**	5

p6	**A**	**B**	**C**	**D**	**E**	**F**	$a_i^{'}$
A	**1**	0	0	1	0	1	3
B	2	**1**	2	1	1	1	8
C	2	0	**1**	2	1	2	8
D	1	1	0	**1**	0	1	4
E	2	1	1	2	**1**	2	9
F	1	1	0	1	0	**1**	4

p7	**A**	**B**	**C**	**D**	**E**	**F**	$a_i^{'}$
A	**1**	0	2	1	0	1	5
B	2	**1**	1	2	1	2	9
C	0	1	**1**	2	1	2	7
D	1	0	0	**1**	0	1	3
E	2	1	1	2	**1**	2	9
F	1	0	0	1	0	**1**	3

p8	**A**	**B**	**C**	**D**	**E**	**F**	$a_i^{'}$
A	**1**	1	0	1	0	1	4
B	1	**1**	1	2	1	2	8
C	2	1	**1**	2	1	2	9
D	1	0	0	**1**	0	1	3
E	2	1	1	2	**1**	2	9
F	1	0	0	1	0	**1**	3

p9	**A**	**B**	**C**	**D**	**E**	**F**	$a_i^{'}$
A	**1**	0	0	1	0	1	3
B	2	**1**	1	2	1	2	9
C	2	1	**1**	2	0	2	8
D	1	0	0	**1**	0	1	3
E	2	1	2	2	**1**	1	9
F	1	0	0	1	1	**1**	4

p10	**A**	**B**	**C**	**D**	**E**	**F**	$a_i^{'}$
A	**1**	0	0	1	0	1	3
B	2	**1**	1	1	1	2	8
C	2	1	**1**	2	0	1	7
D	1	1	0	**1**	0	1	4
E	2	1	2	2	**1**	1	9
F	1	0	1	1	1	**1**	5

Having the tables of ratings of all 10 experts, we then summarized all the ratings in one common table, calculating the sum of the corresponding cells of all the tables. As a result, the sum of the total preferences of each expert per row was determined using the following formula.

$$a_i^{'} = \sum_{j=1}^{n} a_{ij}$$

where the best is considered to be the object to which the maximum sum score corresponds.

Having the table of sums of experts' sum preferences, we then calculated the relative significance of the scores given by each expert, which we will denote by wij:

$$wij = xij \,/ \sum xij$$

Where xij is the score given by expert i to object or factor j.

Table 2

The sum of the experts' total preferences and the relative significance of the estimates

	A	*B*	*C*	*D*	*E*	*F*
p1	5	9	4	4	9	5
p2	4	8	9	3	9	3
p3	4	8	8	3	9	4
p4	3	9	9	3	7	5
p5	4	9	7	4	7	5
p6	3	8	8	4	9	4
p7	5	9	7	3	9	3
p8	4	8	9	3	9	3
p9	3	9	8	3	9	4
p10	3	8	7	4	9	5
xij	38	85	76	34	86	41
wij	0.105556	0.23611111	0.211111	0.094444	0.238889	0.11

According to the data in Table 2, the $\sum xij$=360:

Therefore, to determine the degree of agreement between different experts, assess the reliability of the data, and ensure the validity of the decision-making models, we also calculated the concordance coefficient (Kendall, et al., 1939).

Table 3

Concordance coefficient calculation table

	A	*B*	*C*	*D*	*E*	*F*
p1	3.5	1.5	5.5	5.5	1.5	3.5
p2	4	3	1.5	5.5	1.5	5.5
p3	4.5	2.5	2.5	6	1	4.5
p4	5.5	1.5	1.5	5.5	3	4
p5	6	1	3	5	1.5	4
p6	5.5	2.5	2.5	5.5	2.5	4
p7	4	1.5	3	5.5	1.5	5.5
p8	4	3	1.5	5.5	1.5	5.5
p9	5.5	1.5	3	5.5	1.5	4
p10	6	2	3	5	1	4
A	48.5	20	27	54.5	16.5	44.5

After compiling the concordance table, we also calculated the final concordance coefficient.

Let's denote the average of the total sum scores by B.

$$B = 35.17$$

Then, we calculate **S**.

$$S = (48.5 - 35.17)^2 + (20 - 35.17)^2 + (27 - 35.17)^2 \ldots + \\ +(44.5 - 35.17)^2 = 1283.83$$

$$W_i = \frac{12 * 1283.83}{100 * 210} = 0.733$$

As a result of the calculation, the concordance coefficient was 0.73. Comparing the obtained concordance coefficient with the values in the Magolin scale, we can conclude that the expert assessments have a high level of agreement, therefore, these assessments are fully applicable in the assessment process.

Then, using the weighted average values of the obtained relative significances, we determined the overall assessment of the insurance score. As a result, we have the following model:

$$S = 0.094444 \cdot X1 + 0.236111 \cdot X2 + 0.227778 \cdot X3 + 0.094444 \cdot X4 + \\ + 0.247222 \cdot X5 + 0.11 \cdot X6$$

To assess the practical applicability of the resulting model, we can enter numerical values for the model variables (X_1, X_2, X_3, X_4, X_5, X_6) and calculate the insurance score (S).

To substantiate the applicability of the model obtained based on the analysis, let us also calculate the score based on the indicators provided by one of the companies operating in the market occupying an average position. Before proceeding to the calculation, let us solve one important problem, namely, the values of the indicators selected by us may actually have different scales and units (for example, the number of claims, the amount, the credit score), which makes their comparison and analysis difficult. Therefore, a decision was made jointly with the insurance company to normalize the indicators. Normalization allows for an objective assessment of the riskiness of clients, ensuring the comparability of indicators and increasing the accuracy and efficiency of the scoring model. It should be added that each insurance company can independently set the normalization limits based on their business requirements, risk management strategy and market conditions.

We used the minimum-maximum normalization method, which is a simple and effective method that is widely used in the data preparation process. According to the method, the indicators were normalized based on the following formula.[1]

$$N_i = \frac{X_i - X_{min}}{X_{max} - X_{min}} \times 10$$

- N_i -normalized value of indicator i;
- X_i -raw (original) value of the indicator;
- X_{max} X_{min} -minimum and maximum observed or expert-defined limits;

The 0–10 range was chosen for interpretability and alignment with common credit/insurance scoring practices, where higher values indicate lower risk. This facilitates communication with practitioners and ensures comparability across heterogeneous indicators. Since real client-level insurance data are confidential and difficult to obtain due to competition and data protection regulations, the following calculations are based on synthetic (illustrative) data.

[1] Science Direct. (n.d.). *Max normalization*. Retrieved April 10, 2025, from https://www.sciencedirect.com/topics/computer-science/max-normalization

These example values are used solely for methodological demonstration to verify the internal logic and proportionality of the developed model. Future research will validate the results using real company datasets once access becomes available.

Table 4

Explanation of Observed (Example) Values

Indicator	*Observed value (X_i)*	*Explanation / Interpretation*
A – Payment history	95%	The client has made 95% of all premium payments on time, reflecting a high level of financial discipline and reliability.
B – Credit score	730	The client's credit score is 730, indicating good creditworthiness and a low probability of financial default. It shows stable financial behavior.
C – Fraud history	"No fraud"	The client has no recorded cases of fraud or suspicious activity, reflecting strong ethical behavior and minimal risk of intentional loss.
D – Claims quantity	3	The client has filed three claims per year on average. This is considered moderate claim frequency, indicating a normal level of risk exposure.
E – Claims amount	300,000 AMD	The client's average annual claim amount is about 300,000 AMD, within an acceptable loss range and not indicating excessive damages.
F – Insurance history	10	Represents a perfect insurance history — the client has maintained continuous coverage for several years without contract termination or suspension.

The indicators presented above were then transformed into normalized values using the min–max method. This step ensures that all indicators, regardless of their initial measurement units or qualitative nature, are expressed on the same 0–10 scale. The summarized results of this normalization process are presented in Table 5.

Table 5

Summary of normalized indicator values

Indicator	X_i	X_{min}	X_{max}	N_i
A – Payment history	95%	60	100	9.0
B – Credit score	730	300	850	8.0
C – Fraud history	No fraud	0	10	10.0
D – Claims quantity	3	0	5	6.0
E – Claims amount	300,000	0	1,000,000	7.0
F – Insurance history	10	0	10	10.0

Now, we substitute the values into the formula:

$$S = 0.094444 \cdot 9 + 0.236111 \cdot 8 + 0.227778 \cdot 10 + 0.094444 \cdot 6 + \\ +0.247222 \cdot 7 + 0.11 \cdot 10 = 8.29$$

The customer's score is 8.29 (out of 10).

This result indicates that the client is considered low-risk, as the score is close to the maximum value (10). In international practice, insurance companies use similar scales to assess the riskiness of clients. For example:

- 8.0 – 10.0: Low Risk
- 5.0 – 7.9: Medium Risk

- 2.0 – 4.9: High Risk
- 0.0 – 1.9: Very High Risk

A client's score of 8.2 indicates that he or she belongs to the low-risk category. This result is of great importance in various areas of the insurance company's activities.

1. Risk management. Low-risk customers reduce the company's risk burden, which allows for more efficient resource management and reduced need for reserve capital.
2. Tariff policy. Low-risk customers can be offered more favorable terms, such as lower insurance premiums or additional coverage. This helps to strengthen customer loyalty and increase the company's competitiveness.
3. Asset management. The presence of low-risk customers allows the company to invest more funds in long-term and high-yield investments, which improves financial stability and profitability.
4. Loss reduction. Low-risk customers tend to make fewer claims, which reduces the company's loss and increases profitability.
5. Customer loyalty. Offering favorable terms to low-risk customers helps to strengthen their loyalty, which is important for the development of long-term relationships.

It should be added that the model is designed for customers who have at least one year of history in insurance activities. Customers who do not yet have one year of history are recommended to use averaged data or a preliminary estimate until they accumulate sufficient data. This approach allows one to reduce risks, provide a more accurate estimate over time, and adjust the applicability of the model to all customers.

CONCLUSION. As a result of the expert assessment, an insurance score assessment methodology was formed, where the indicators were classified according to their degree of impact. The developed model, which is based on Pairwise Comparison Analysis and Analytical Hierarchy Process (AHP), is ready for practical application and is recommended for companies operating in the Armenian insurance market. It will allow insurance companies to:

1. Classify customers by risk level based on objective and systematic criteria.
2. Predict potential losses, reducing loss rates and improving risk management strategies.
3. Implement effective asset management, ensuring more stable and profitable operations.

The research contributes to the introduction of a scoring system in the Armenian insurance market, based on international best practices and local conditions. The proposed model can improve the effectiveness of risk management, reduce loss rates, and ensure a more accurate and fair tariff policy. In the future, additional factors can be studied, such as:

- Social media data for deeper analysis of customer behavior and risk.
- Behavioral characteristics for studying customer decision-making and consumption patterns.
- Expanding the applicability of the model to other types of insurance (e.g. health).

However, the study also has several limitations. The expert sample consisted of only ten specialists, reflecting the limited number of qualified professionals in the Armenian insurance market and the difficulty of involving them in the research. Moreover, the model relies primarily on expert judgments rather than real company data, which may introduce a certain degree of subjectivity. These limitations, however, do not diminish the practical value of the findings but rather indicate directions for future improvement.

This research can be considered the first step in the development and implementation of a scoring system in Armenia. It has great potential to improve the efficiency and long-term sustainability of insurance companies. A stable and effective scoring system will not only reduce risks, but also increase customer trust and satisfaction, which is important for maintaining competitiveness in the market and keeping up with the global pace.

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