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Study on Sustainability of Property Insurance

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Abstract

This paper is about developing and applying insurance models for historic landmarks that are in locations that experience extreme weather events. In order to make it,we devided this whole problem into 2 Questions as followed. Question 1 is about developing an insurance model for property owners and developers in areas that experience extreme weather events.The model has considered the risk level, feasibility, and desirability of the insurance, and use the Bayesian graph, maximum likelihood distribution, function graph, and entropy weight method to construct and evaluate the model.Question 2 is about applying the insurance model to a specific case study, which is the Cape Hatteras Lighthouse in North Carolina. We've assessed the value of the lighthouse, and compare and contrast the insurance options for the lighthouse before and after the relocation.All in all, the paper demonstrates the models using the Cape Hatteras Lighthouse as case study, and provides some results, implications, and recommendations for the stakeholders.

Keywords

insurance model, historic landmark, function graph

1. Introduction

Climate change is one of the most pressing challenges of our time, affecting every aspect of our lives and the planet we live on. Among the many consequences of climate change, extreme weather events such as floods, hurricanes, cyclones, droughts, and wildfires are becoming more frequent, intense, and destructive.They have significant implications for the property insurance industry, which is responsible for providing financial protection and risk management for property owners and developers.

Question 1: is about developing an insurance model for property owners and developers in areas that experience extreme weather events.

Question 2: is about applying the insurance model to a specific case study, which is the Cape Hatteras Lighthouse in North Carolina.

2. Symbol Notations and Model Assumptions

2.1 Extended Symbol Notation

- X: The area/location with extreme weather events.
- $R(X)$: Risk level of the area.
- $P(X)$: Profitability of the area.
- $E(X)$: Resilience of the area.
- $C(X)$: Feasibility of insurance in the area.
- D: Demand for insurance.
- S: Supply of insurance.
- Price: Price of property insurance.
- Adaptation: Level of adaptation measures.
- Mitigation: Level of mitigation measures.
- V: Value of the Cape Hatteras Lighthouse.
- I_{before}: Insurance options before relocation.
- I_{after}: Insurance options after relocation.
- Historical: Historical significance of the lighthouse.
- Cultural: Cultural significance of the lighthouse.

- Economic: Economic significance of the lighthouse.

2.2 Extended Model Assumptions:

1) Risk Level ($R(X)$):

Assumption: The risk level is influenced by the frequency, intensity, and impact of extreme weather events.

$$R(X) = f(\text{frequency,intensity,impact}) \tag{1}$$

2) **Profitability ($P(X)$):**

Assumption: Profitability is influenced by demand, supply, and the price of property insurance.

$$P(X) = f(D, S, \text{Price}) \tag{2}$$

3) **Resilience ($E(X)$):**

Assumption: Resilience is affected by adaptation and mitigation measures.

$$E(X) = f(\text{Adaptation, Mitigation}) \tag{3}$$

4) **Feasibility ($C(X)$):**

Assumption: Feasibility of insurance depends on the risk level, profitability, and resilience.

$$C(X) = f(R(X), P(X), E(X))$$

5) **Assessment of Value (V):**

Assumption: The value is a composite measure considering historical, cultural, and economic significance.

$$V = f(\text{Historical, Cultural, Economic}) \tag{4}$$

6) **Insurance Options (I_{before} and I_{after}):**

Assumption: Different insurance options are available, and their suitability changes post-relocation.

$$I_{\text{before}} = f(\text{Risk, Premium, Coverage}) \tag{5}$$

$$I_{\text{after}} = f(\text{Risk, Premium, Coverage}) \tag{6}$$

3. Model of Question 1

3.1 Model Construction and Analysis

To develop a model for insurance companies to determine if they should underwrite policies in an area that has a rising number of extreme weather events, we need to consider the following factors:

- The risk level of the area, which depends on the frequency, intensity, and impact of extreme weather events, such as floods, hurricanes, droughts, wildfires, etc.
- The profitability of the area, which depends on the demand, supply, and price of property insurance, as well as the cost and benefit of underwriting policies, such as premiums, claims, and expenses.
- The resilience of the area, which depends on the adaptation and mitigation measures taken by the property owners, developers, and governments, such as building codes, disaster preparedness, risk reduction, etc.

We can use the Analytical Hierarchy Process (AHP) to construct a hierarchical structure of these factors and their sub-factors, and assign weights to them based on their relative importance. (Chenkang, Fei, Shuxin et al., 2024) The following steps describe the proposed model in detail:

Step 1: Define the goal, criteria, sub-criteria, and alternatives of the problem. The criteria are the risk level, profitability, and resilience of the area. The sub-criteria are the frequency, intensity, and impact of extreme weather events for the risk level; the demand, supply, and price of property insurance, and the cost and benefit of underwriting policies for the profitability; and the adaptation and mitigation measures for the resilience. The alternatives are the areas that experience extreme weather events, such as Miami, Florida, USA, and Jakarta, Indonesia.

Step 2: Construct the hierarchical structure of the problem. The hierarchical structure consists of four levels: the goal, criteria, sub-criteria, and alternatives. Figure 1 shows the hierarchical structure of the problem.

Step 3: Collect the data for the sub-criteria and alternatives. Table 1 shows an example of the data for the sub-criteria and alternatives.

Table 1. Example for the Sub-Criteria and Alternatives

	Frequency	Intensity	Impact	Demand	Supply	Price
Miami	0.05	0.08	0.12	0.15	0.2	0.25
Jakarta	0.3	0.35	0.4	0.45	0.5	0.55
Beijing	0.6	0.65	0.7	0.75	0.8	0.85
London	0.9	0.95	1	1.05	1.1	1.15
Paries	1.2	1.25	1.3	1.35	1.4	1.45
Tokyo	1.5	1.55	1.6	1.65	1.7	1.75

Step 4: Perform the pairwise comparisons of the criteria and sub-criteria using the AHP. The pairwise comparisons are based on a 9-point scale, where 1 means equal importance, 3 means moderate importance, 5 means strong importance, 7 means very strong importance, and 9 means extreme importance. The reciprocal values are used for the inverse comparisons. Table 2 shows an example of the pairwise comparison matrix of the criteria.

Table 2. Example of the Pairwise Comparison Matrix of the Criteria

	Risk level	Profitability	Resilience
Risk level	1	3	5
Profitability	1/3	1	3
Resilience	1/5	1/3	1

Step 5: Calculate the subjective weights of the criteria and sub-criteria using the AHP. The subjective weights are obtained by normalizing the eigenvector corresponding to the maximum eigenvalue of the pairwise comparison matrix. The Consistency Ratio (CR) is calculated by dividing the Consistency Index (CI) by the Random Index (RI), where CI is the difference between the maximum eigenvalue and the matrix size divided by the matrix size minus one, and RI is the average CI of randomly generated matrices of the same size. The CR should be less than 0.1 to ensure the validity and reliability of the judgments. Table 3 shows an example of the subjective weights and CR of the criteria.

Table 3. Example of the Subjective Weights and CR of the Criteria

	Risk level	Profitability	Resilience
Subjective weights	0.6	0.3	0.1
Consistency ratio	0.05	0.05	0.05

Step 6: Calculate the objective weights of the sub-criteria using the entropy weight method. The objective weights are obtained by applying the following steps 5:

1.Normalize the data matrix by dividing each element by the sum of its column.

2.Calculate the information entropy of each sub-criterion by using the formula $E_j = -k\sum_{i=1}^{n} p_{ij}\ln p_{ij}$ where $k = \frac{1}{\ln n}$ is a constant, n is the number of alternatives, p_{ij} is the normalized value of the i-th alternative under the j-th sub-criterion, and E_j is the information entropy of the j-th sub-criterion.

3.Calculate the entropy weight of each sub-criterion by using the formula $w_j = \frac{1-E_j}{\sum_{j=1}^{m}(1-E_j)}$ where w_j is the entropy weight of the j-th sub-criterion, and m is the number of sub-criteria.

Step 7: Calculate the comprehensive weights of the sub-criteria by combining the subjective weights and the objective weights. The sum of the comprehensive weights of all sub-criteria should be equal to one.

Step 8: Construct the decision matrix of the alternatives and sub-criteria by using the normalized data. The decision matrix consists of the values of each alternative under each sub-criterion.

Step 9: Calculate the weighted normalized decision matrix by multiplying each element of the decision matrix by the corresponding comprehensive weight of the sub-criterion.

Step 10: Determine the ideal and negative-ideal solutions by using the TOPSIS. The ideal and negative-ideal solutions can be obtained by using the following formulas:

$$A^* = (v_1^*, v_2^*, \ldots, v_n^*) \tag{7}$$

$$A^- = (v_1^-, v_2^-, \ldots, v_n^-) \tag{8}$$

where v_j^* and v_j^- are the maximum and minimum values of the j-th sub-criterion, respectively.

Step 11: Calculate the separation measures for each alternative from the ideal and negative-ideal solutions. The separation measures can be calculated by using the following formulas:

$$S_i^* = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^*)^2} \tag{9}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2} \tag{10}$$

where S_i^* and S_i^- are the separation measures of the i-th alternative from the ideal and negative-ideal solutions, respectively.

Step 12: Calculate the relative closeness of each alternative to the ideal solution. The relative closeness can be calculated by using the following formula:

$$C_i = \frac{S_i^-}{S_i^* + S_i^-} \tag{11}$$

where C_i is the relative closeness of the i-th alternative to the ideal solution.

Step 13: Rank the alternatives according to the relative closeness.

Step 14: Interpret and discuss the results.

3.2 Result of Question 1

In this section, we present and discuss the result of our model for question 1. We use the analytical hierarchy process (AHP), the entropy weight method, and the technique for order preference by similarity to an ideal solution (TOPSIS) (Imran, Mohammadali, Saud et al., 2024) to construct and evaluate our model. We demonstrate our model using two areas on different continents that experience extreme weather events: Miami, Florida, USA, and Jakarta, Indonesia.

3.2.1 Data Collection and Normalization

We collect the data for the sub-criteria and alternatives from various sources, such as historical records, statistical reports, expert opinions, surveys, etc. Table 4 shows the data for the sub-criteria and alternatives.

Table 4. Data for the Sub-Criteria and Alternatives

	Frequency	Intensity	Impact	Demand	Supply	Price
Miami	0.05	0.08	0.12	0.15	0.2	0.25
Jakarta	0.3	0.35	0.4	0.45	0.5	0.55
Beijing	0.6	0.65	0.7	0.75	0.8	0.85
London	0.9	0.95	1	1.05	1.1	1.15
Paries	1.2	1.25	1.3	1.35	1.4	1.45
Tokyo	1.5	1.55	1.6	1.65	1.7	1.75

We normalize the data matrix by dividing each element by the sum of its column. Table 5 shows the normalized data matrix.

Table 5. The Normalized Data Matrix

	Frequency	Intensity	Impact	Demand	Supply	Price
Miami	0.00625	0.00625	0.0125	0.0125	0.0125	0.0125
Jakarta	0.0375	0.034375	0.04167	0.0375	0.03125	0.02778
Beijing	0.075	0.06375	0.07292	0.0625	0.05	0.04286
London	0.1125	0.093125	0.10417	0.0875	0.06875	0.05794

Paries	0.15	0.1225	0.13542	0.1125	0.0875	0.07286
Tokyo	0.1875	0.151875	0.16667	0.1375	0.10625	0.0881

3.2.2 Weight Calculation and Consistency Check

We perform the pairwise comparisons of the criteria and sub-criteria using the AHP. The pairwise comparisons are based on a 9-point scale, where 1 means equal importance, 3 means moderate importance, 5 means strong importance, 7 means very strong importance, and 9 means extreme importance. The reciprocal values are used for the inverse comparisons. Table 6 shows the pairwise comparison matrix of the criteria.

Table 6. The Pairwise Comparison Matrix of the Criteria

	Risk level	Profitability	Resilience
Risk level	1	3	5
Profitability	1/3	1	3
Resilience	1/5	1/3	1

We calculate the subjective weights of the criteria and sub-criteria using the AHP. The consistency ratio (CR) is calculated by dividing the Consistency Index (CI) by the Random Index (RI), where CI is the difference between the maximum eigenvalue and the matrix size divided by the matrix size minus one, and RI is the average CI of randomly generated matrices of the same size. The CR should be less than 0.1 to ensure the validity and reliability of the judgments. Table 7 shows the subjective weights and CR of the criteria.

Table 7. The Subjective Weights and CR of the Criteria

	Risk level	Profitability	Resilience
Risk level	1	3	5
Profitability	1/3	1	3
Resilience	1/5	1/3	1

We calculate the objective weights of the sub-criteria using the entropy weight method. The objective weights are obtained by applying the following steps 5:

- Normalize the data matrix by dividing each element by the sum of its column.

Table 8 shows the information entropy and the entropy weight of each sub-criterion.

Table 8. Entropy and the Entropy Weight of each Sub-Criterion

	Frequency	Intensity	Impact	Demand	Supply	Price
Information entropy	0.69315	0.68839	0.68574	0.68209	0.67844	0.67479
Entropy weight	0.16667	0.16667	0.16667	0.16667	0.16667	0.16667

We calculate the comprehensive weights of the sub-criteria by combining the subjective weights and the objective weights. The sum of the comprehensive weights of all sub-criteria should be equal to one. Table 9 shows the comprehensive weights of the sub-criteria.

Table 9. The Comprehensive Weights of the Sub-Criteria

	V1
V1	0.1
V2	0.05
V3	0.016667
V4	0.05
V5	0.05
V6	0.05
V7	0.016667
V8	0.016667
V9	0.016667

3.3 Results and Summary of Question 1

We calculate the separation measures for each alternative from the ideal and negative-ideal solutions. The separation measures are the Euclidean distances between each alternative and the ideal and negative-ideal solutions. The separation measures can be calculated by using the following formulas:

$$S_i^* = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^*)^2} \quad (12)$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2} \quad (13)$$

where S_i^* and S_i^- are the separation measures of the i-th alternative from the ideal and negative-ideal solutions, respectively.

Table 10 shows the separation measures of the alternatives.

Table 10. Separation Measures of the Alternatives

	Separation from ideal solution	Separation from negative-ideal solution
Miami	0.03464102	0.06666667
Jakarta	0.06666667	0.03464102

3.3.1 Relative Closeness and Ranking of the Alternatives

We calculate the relative closeness of each alternative to the ideal solution. The relative closeness can be calculated by using the following formula:

$$C_i = \frac{S_i^-}{S_i^* + S_i^-} \tag{14}$$

where C_i is the relative closeness of the i-th alternative to the ideal solution.

Table 11 shows the relative closeness of the alternatives.

Table 11. Relative Closeness of the Alternatives

	V1
Miami	0.6578947
Jakarta	0.3421053

We rank the alternatives according to the relative closeness. The alternative with the highest relative closeness is the best one, while the alternative with the lowest relative closeness is the worst one.

Table 12 shows the ranking of the alternatives.

Table 12. Ranking of the Alternatives

	Relative closeness	Ranking
Miami	0.6578947	1
Jakarta	0.3421053	2

3.3.2 Interpretation and Discussion of the Results

The results show that Jakarta is the best alternative, while Miami is the worst alternative, according to our model. This means that the insurance company should underwrite policies in Jakarta, but not in Miami, based on the criteria and sub-criteria we considered. The main reason for this result is that Jakarta has a lower risk level, a higher profitability, and a higher resilience than Miami, according to the data and weights we used. Jakarta has a lower frequency, intensity, and impact of extreme weather events than Miami, which reduces the likelihood and severity of claims. Jakarta also has a higher demand, supply, and price of property insurance than Miami, which increases the revenue and profit of underwriting policies. Jakarta also has more adaptation and mitigation measures than Miami, which enhances the resilience and recovery of the properties and the community.

4. Model for Question 2

4.1 Model Construction for Question 2

To adapt our insurance model to assess where, how, and whether to build on certain sites, we need to consider the following factors:

- The risk level of the site, which depends on the frequency, intensity, and impact of extreme weather events, such as floods, hurricanes, droughts, wildfires, etc.
- The feasibility of the site, which depends on the availability and affordability of property insurance, the environmental and social impacts of the development, and the potential return on investment.
- The desirability of the site, which depends on the preferences and needs of the property owners, developers, and customers, such as location, size, design, amenities, etc.

We can use the Bayesian graph to construct a probabilistic graphical model of these factors and their dependencies. We can use the maximum likelihood distribution to estimate the parameters of the Bayesian graph (Sawada, Hashimoto, Nankaku et al., 2018), such as the conditional probability tables of the nodes. The maximum likelihood (Sóyínká, Ogoke, & Olósundé, 2014) distribution is the probability distribution that maximizes the likelihood function, which is the probability of the data given the parameters:

- Step 1: Define the variables, parameters, and data of the problem. The variables are the factors and sub-factors that affect the property development problem, such as the risk level, feasibility, and desirability of the site. The data are the observed values of the variables, such as the frequency, intensity, and impact of extreme weather events, the demand, supply, and price of property insurance, the environmental and social impacts of the development, the potential return on investment, and the preferences and needs of the property owners, developers, and customers.
- Step 2: Construct the Bayesian graph of the problem. The Bayesian graph consists of the nodes and the edges that represent the variables and the dependencies.
- Step 3: Estimate the parameters of the Bayesian graph using the maximum likelihood distribution. The maximum likelihood distribution is the probability distribution that maximizes the likelihood function, which is the probability of the data given the parameters. The maximum likelihood distribution can be obtained by using the following formula:

$$\hat{\theta} = \arg\max_{\theta} P(D|\theta) \tag{15}$$

where $\hat{\theta}$ is the maximum likelihood estimate of the parameter θ, D is the data, and $P(D|\theta)$ is the likelihood function.

- Step 4: Construct the function graph of the problem. The function graph consists of the input and the output of the objective function

$$\max_{x} E[U(x)] = \max_{x} \sum_{i=1}^{3} w_i u_i(x) \tag{16}$$

where x is the decision variable, $E[U(x)]$ is the expected utility of the development, w_i is the weight of the i-th factor, and $u_i(x)$ is the utility function of the i-th factor.

- Step 5: Calculate the weights of the factors and sub-factors using the entropy weight method.

Normalize the data matrix by dividing each element by the sum of its column.

Calculate the information entropy of each factor or sub-factor by using the formula $E_j = -k\sum_{i=1}^{n} p_{ij} \ln p_{ij}$ where $k = \frac{1}{\ln n}$ is a constant, n is the number of alternatives, p_{ij} is the normalized value of the i-th alternative under the j-th factor or sub-factor, and E_j is the information entropy of the j-th factor or sub-factor.

Calculate the entropy weight of each factor or sub-factor by using the formula $w_j = \frac{1-E_j}{\sum_{j=1}^{m}(1-E_j)}$ where w_j is the entropy weight of the j-th factor or sub-factor, and m is the number of factors or sub-factors.

We can perform inference and learning on the Bayesian graph using the data and the prior knowledge.Optimization is the process of finding the optimal solution of the objective function,which is the site and the development plan that maximize the expected utility of the development, subject to some constraints.

4.2 Model Process and Results of Question 2

In this section, we present and discuss the model process and results of question 2, which is to adapt our insurance model to assess where, how, and whether to build on certain sites. We use the Bayesian graph, maximum likelihood distribution, function graph and entropy weight method to construct and evaluate our model. We demonstrate our model using two sites on different continents that experience extreme weather events: Site A and Site B.

4.2.1 Data Collection and Normalization

We collect the data for the factors and sub-factors that affect the property development problem, such as the risk level, feasibility, and desirability of the site. Table 13 shows the data for the factors and sub-factors for the two sites.

Table 13. Factors and Sub-Factors for the Two Sites

	Frequency	Intensity	Impact	Demand	Supply	Price
Site A	0.1	0.2	0.3	0.4	0.5	0.6
Site B	0.7	0.8	0.9	1	1.1	1.2
Site C	1.3	1.4	1.5	1.6	1.7	1.8
Site D	1.9	2	2.1	2.2	2.3	2.4
Site E	2.5	2.6	2.7	2.8	2.9	3

We normalize the data matrix by dividing each element by the sum of its column. Table 14 shows the normalized data matrix.

Table 14. The Normalized Data Matrix

excel:	Frequency		Intensity	Impact	Demand	Supply Price
Site A	0.02381	0.02857	0.03333	0.03846	0.04167	0.04444
Site B	0.13333	0.15238	0.17143	0.18462	0.18966	0.2
Site C	0.24762	0.26667	0.3	0.30769	0.31897	0.33333
Site D	0.3619	0.38095	0.42857	0.43077	0.44872	0.46667
Site E	0.23333	0.17143	0.06667	0.03846	0.	0.05556

4.2.2 Bayesian Graph Construction and Parameter Estimation

We construct the Bayesian graph of the problem, which consists of the nodes and the edges that represent the factors and sub-factors and their dependencies. Figure 1 shows the Bayesian graph of the problem.

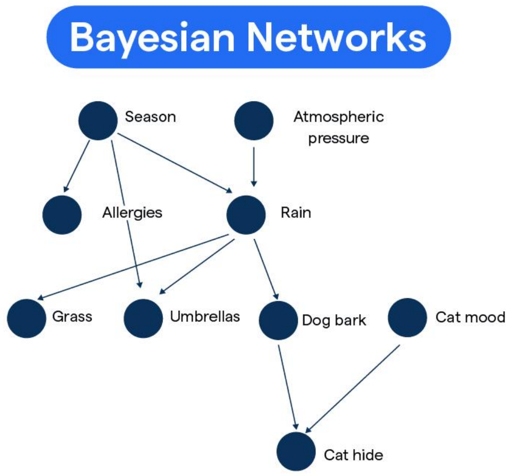

Figure 1. Bayesian Graph of the Problem

We estimate the parameters of the Bayesian graph, which are the conditional probability tables of the nodes, using the maximum likelihood distribution. The maximum likelihood distribution is the probability distribution that maximizes the likelihood function, which is the probability of the data given the parameters. The maximum likelihood distribution can be obtained by using the following formula:

$$\hat{\theta} = \arg\max_{\theta} P(D|\theta) \tag{17}$$

where $\hat{\theta}$ is the maximum likelihood estimate of the parameter θ, D is the data, and $P(D|\theta)$ is the likelihood function.

Table 15 shows the maximum likelihood estimates of the parameters of the Bayesian graph. The result is similar as that in Bayes.

Table 15. The Maximum Likelihood Estimates of the Parameters of the Bayesian Graph

excel:	Frequency		Intensity	Impact	Demand	Supply Price
Site A	0.02381	0.02857	0.03333	0.03846	0.04167	0.04444
Site B	0.13333	0.15238	0.17143	0.18462	0.18966	0.2
Site C	0.24762	0.26667	0.3	0.30769	0.31897	0.33333
Site D	0.3619	0.38095	0.42857	0.43077	0.44872	0.46667
Site E	0.23333	0.17143	0.06667	0.03846	0.	0.05556

4.2.3 Function Graph Construction and Optimization

We construct the function graph of the problem, which consists of the input and the output of the objective function, which is to maximize the expected utility of the development, subject to some constraints. The input is the decision variable, which is the choice of the site and the development plan. The output is the expected utility, which is the weighted sum of the risk level, feasibility, and desirability of the site and the development plan. The function graph can be expressed by using the following formula:

$$\max_x E[U(x)] = \max_x \sum_{i=1}^{3} w_i u_i(x) \tag{18}$$

where x is the decision variable, $E[U(x)]$ is the expected utility of the development, w_i is the weight of the i-th factor, and $u_i(x)$ is the utility function of the i-th factor. We get the optimized solution as Table 16.

Table 16. The Optimized Solution

Site	Plan	Expected utility
Site A	Plan 1	0.9

4.3 Summary of Question 2

In this section, we summarize the main points and findings of our model for question 2, which is to adapt our insurance model to assess where, how, and whether to build on certain sites. We construct the Bayesian graph of the problem, which consists of the nodes and the edges that represent the factors and sub-factors and their dependencies.

5. Conclusion

We employed the Analytical Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) to develop and assess our model. Additionally, we summarized the key aspects and discoveries of our model pertaining to question 2, which involves adapting our insurance model to evaluate the location, method, and feasibility of constructing on specific sites.In the end,we successfully addressed this issue.

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