Analytic Hierarchy Process with the Correlation Effect via WordNet

Jih-Jeng Huang

Abstract: The analytic hierarchy process (AHP) is a well-known approach in decision-making because of its simplicity and rationality. However, in conventional AHP, it cannot account for the correlation effect between criteria. In this paper, we use the lexical database, WordNet, to calculate the similarity between criteria set by a decision-maker. Then, we use the similarity matrix to process the factor analysis and obtain the independent factors, which are composed of their criteria. Finally, the weights of factors are derived to evaluate the alternatives. Moreover, we use a case study of online shopping to illustrate the proposed method and compare the result with the conventional AHP.

Keywords: analytic hierarchy process; independent criteria; WordNet; synset; factor analysis

1. Introduction

The analytic hierarchy/network process (AHP/ANP) [1–3] is a well-known approach to handle multi-criteria decision-making (MCDM) problems. The major distinction between them is that the ANP is viewed as a general form of the AHP to account for interdependent and feedback effects, instead of the independent criteria, as in the AHP. However, the ANP takes more work than the AHP to form the supermatrix, representing the influence degrees between criteria. Hence, the AHP is still a popular contemporary approach in practice to deal with various decision-making problems [4–6].

Many papers have extended the AHP/ANP by considering more complicated issues, such as fuzzy and gray environments [7–9], group-decision problems [10], or integrated with other methods [11–13]. However, there are still a lot of issues that the AHP/ANP should be considered, such as consistency problems [14], independence of the irrelevant alternative (IIA)/rank reversal problems [15], and revised scales in the AHP [16–18]. The problem of the correlated criteria seems to be ignored in the past papers, but see Liu et al. [19] to reflect the influence of the final decision-making. In Liu et al. [19], they simply asked an expert to quantify the correlation between criteria, then using the two-objective programming model to derive the result of the AHP. However, it is still a complicated problem to ensure that the correlations between criteria are rational and correct because it is the subjective judgment by an expert. Hence, it is a crucial problem to account for the correlated effect between criteria in the AHP with the objective calibration and rational result.

We should highlight the differences between interdependency and the correlation between criteria as follows. Interdependent criteria describe how one criterion affects another and is handled by the ANP [3]. Interdependency is a stronger assumption which presents which criterion affects another. In contrast, the correlation is a weak assumption and indicates that these criteria have a common factor affecting alternatives. Hence, we might have no information about the interdependency among criteria, but know the correlation between criteria.

Hence, in this paper, we proposed an extended AHP, which accounts for the correlation effect between criteria. The main idea is that we first calculate the correlation coefficients between criteria via the WordNet database. Note that the database is a lexical dataset that
describes the relationships of words with a tree structure. Hence, we do not need an expert to quantify the correlation between criteria but directly calculate the criteria similarity using some graph-based indexes. Then, we used the factor analysis to derive the independent factors that composed their owned criteria based on factor loadings. Furthermore, we used the conventional AHP to derive the weights of the criteria. Finally, we can calculate the weights of the factors by the product of the factor loadings and weights of the criteria. We use a case study of online shopping to illustrate the proposed method and compare the result with the conventional AHP. The result shows the possible problems of the conventional AHP and justifies the proposed method.

The preference dependence between criteria is the reason why we can use the additive utility function, according to Keeney & Raiffa [20]. However, the postulation here is preferential independence between criteria equivalent to the semantic independence between criteria, and vice versa. Let us give an example to illustrate the above postulation. Two criteria of a problem are durability and quality, the semantic meaning of durability is “permanence by virtue of the power to resist stress or force”, and quality is “a degree or grade of excellence or worth”. For a rational person, if the semantic meanings of durability and quality are considered to be correlated, we usually do not think the criteria are possibly preferentially independent if no further information is available, and vice versa. Surely, if we have collected data about the decision table, we can verify whether the criteria are independent or not based on the theory of preferential independence. However, in the AHP situation, we usually have no such information about the data. Hence, the postulation here is for practical consideration. In addition, we also ask the decision-maker or expert to determine the meaning of a criterion to ensure the correctness of the above inference.

The rest of the paper is organized as follows. The framework of the AHP is first introduced, and the problems of the AHP are highlighted. Next, we propose the revised framework of the AHP to consider the correlation effect between criteria via WordNet. Then, we give a case study to illustrate the proposed method and compare the result with the conventional AHP. Furthermore, we propose the discussion based on the result of the case study. Finally, we present the conclusions of the paper.

2. The Framework of the AHP

The framework of the AHP can be decomposed into different levels of the hierarchical structure, as shown in Figure 1. The first level of the framework indicates the decision’s goal, i.e., purchasing or evaluation decision. The second level of the framework includes factors that affect the decision behavior of the goal, and these factors are composed of exclusive criteria on the third level. The fourth level contains the alternatives of the candidate set. Note that we can indeed add more levels to consider sub-criteria in the framework.

The AHP process starts from quantifying $a_{ij}$, where $A = [a_{ij}]_{n \times n}$, by using a decision-maker to estimate $w_{ij}$ and calculating the weights of the criteria by finding the eigenvector $w$ for the largest eigenvalue, $\lambda_{\text{max}}$, which satisfies the following equation:

$$Aw = \lambda_{\text{max}}w$$

(1)

Additionally, we should verify whether the quantified $a_{ij}$ is consistent and rational enough to approximate $W$. In general, we can use the consistency index ($CI$) and the consistency ratio ($CR$) to check if the consistency condition is satisfied. The $CI$ is calculated as:

$$CI = \frac{(\lambda_{\text{max}} - n)}{(n - 1)}$$

(2)
The framework of the analytic hierarchy process (AHP) starts from quantifying $a_{ij}$, where $A^{n \times n}$ is estimated by a decision-maker to calculate the weights of the criteria by finding the eigenvector $w$ for the largest eigenvalue, $\lambda_{\text{max}}$, which satisfies the following equation:

$$\lambda_{\text{max}} = Aw = w$$  \hspace{1cm} (1)

Additionally, we should verify whether the quantified $a_{ij}$ is consistent and rational enough to approximate $W$. In general, we can use the consistency index ($CI$) and the consistency ratio ($CR$) to check if the consistency condition is satisfied. The $CI$ is calculated as:

$$CI = \frac{n \lambda_{\text{max}} - n}{n - 1}$$  \hspace{1cm} (2)

where $\lambda_{\text{max}}$ is the largest eigenvalue, and $n$ denotes the numbers of the attributes. The formula of $CR$ is:

$$CR = \frac{CI}{RI}$$  \hspace{1cm} (3)

where $RI$ is the random index. The random index is a constant and can refer to the random index table, as shown in Table 1.

### Table 1. The random index table.

| $n$ | One | Two | Three | Four | Five | Six | Seven | Eight | Night |
|-----|-----|-----|-------|------|------|-----|-------|-------|-------|
| $RI$ | 0.00 | 0.00 | 0.58 | 0.90 | 1.12 | 1.24 | 1.32 | 1.41 | 1.46 |

Note that $n$ denotes the number of criteria. Saaty [21] suggested that the value of the $CI$ and $CR$ should not exceed 0.1 for a reliable result.

The concerned problem in this paper is the independent assumption of factors and criteria in the AHP. The independence between factors or criteria is the consideration of simple calculation, although it might not be reasonable in practice. The irrational postulation we are concerned about here is that if a factor can be divided into several criteria/sub-criteria, these criteria/sub-criteria usually have some common properties; otherwise, they should agglomerate into the same factor. In addition, even though Saaty [3] suggested using the analytic network process (ANP) to consider the interdependence and feedback effects between criteria, it hugely complicates the pairwise comparison between criteria to form a supermatrix. Hence, we need a revision of the AHP to solve the above issues.

### 3. Revised Framework of the AHP

The revised framework of the AHP in this paper is represented as a three-level hierarchical structure composed of the goal, factors, and alternatives. The reason that factors are independent of each other is not postulated by the assumption but the statistical theory. The major difference from the original AHP framework is that alternatives are affected by factors rather than criteria, as shown in Figure 2.
The framework here is based on factors that are usually used for evaluating alternatives rather than criteria, i.e., purchase decision models. For example, many papers [22,23] indicate that online buying behavior is affected by the two factors, perceived benefits and perceived risks [24], where perceived benefits include shopping convenience, product selection, and ease/comfort of shopping, and hedonic and perceived risks include financial risk, product risk, and time risk. If we use criteria rather than factors in evaluating alternatives, we might over/underweight some factors because we consider the different number of criteria for factors. For example, suppose we consider four criteria of perceived benefits and two criteria of perceived risks. In that case, the best choice might overweight the importance of perceived benefit and underweight the importance of perceived risk.

Hence, we consider using the exploratory factor analysis to agglomerate criteria into factors, where factors have distinct criteria to represent the factor’s content, as shown in Figure 3. Note that $\varepsilon$ denotes the error or specific factor regarding a criterion that can be ignored to represent the factor.

Figure 2. Revised framework of the AHP.

Figure 3. Concept of exploratory factor analysis.

However, the above framework cannot be processed in the conventional AHP because we need the correlation matrix of criteria, which cannot be obtained, to run the exploratory factor analysis. Hence, we introduce the natural language process (NLP) tools to solve the above problem.
3.1. WordNet

WordNet is an extensive lexical dictionary of English which groups nouns, verb, adjectives, and adverbs into sets of cognitive synonyms, called synset, to represent semantic relationships between words with the tree structure. Take the term price, for example. We can find the direct hypernym of price as cost, and the direct hyponym as asking/selling price, bid price, closing price, factory price, highway robbery, purchase price, spot/cash price, support level, and valuation to form the tree structure as shown in Figure 4:

![Synset structure of WordNet.](image_url)

**Figure 4.** Synset structure of WordNet.

Before calculating the similarity between criteria, we should first ask a decision-maker or expert to define the meaning of the criterion. Take the word “price”, for example. We can use WordNet to check the definitions of “price”, and the first three definitions are:

- The property of having material worth (often indicated by the amount of money something would bring if sold);
- The amount of money needed to purchase something;
- The value measured by what must be given or done or undergone to obtain something.

On the other hand, if we use the word “cost” to check its definitions via WordNet, we can obtain:

- The total spent for goods or services, including money and time and labor;
- The property of having material worth (often indicated by the amount of money something would bring if sold);
- The value measured by what must be given or done or undergone to obtain something.

Clearly, the criteria similarity between price and cost depends on which definitions we choose with respect to the words price and cost. Therefore, we should clearly define our criteria before we process the AHP with the correlated criteria.

In this paper, the definitions of criteria about a goal are set as follows. First, we will ask the experts to mark the definitions of criteria from our lists. For example, we ask an expert to give the definitions of every criterion, as shown in Table 2:

Once we obtain the definitions of criteria, we can calculate the similarity/correlation between criteria.

3.2. Word Similarity

Several word similarity measurements can be used for the graph-based structure of semantic words in the WordNet structure. Next, we introduce some of them as follows:

Wu and Palmer similarity [25] measures the depth of two given words, i.e., \( s_1, s_2 \), in the WordNet synset, and the least common subsumer (LCS) by the following formula:

\[
WS = 2 \times \frac{\text{depth}(\text{LCS}(s_1, s_2))}{\text{depth}(s_1) + \text{depth}(s_2)}
\]  
(4)
Table 2. Definitions of criteria.

| Criteria | Definitions |
|----------|-------------|
| Price    | □ The property of having material worth (often indicated by the amount of money something would bring if sold); □ The amount of money needed to purchase something; □ The value measured by what must be given or done or undergone to obtain something. |
| Quality  | □ An essential and distinguishing attribute of something or someone; □ A degree or grade of excellence or worth; □ A characteristic property that defines the apparent individual nature of something. |
| Service  | □ Work done by one person or group that benefits another; □ An act of help or assistance; □ The act of public worship following prescribed rules. |

where \( WS \in (0, 1] \) denotes the similarity score of \( s_1 \) and \( s_2 \), and \( lcs(\cdot) \) is the LCS operator. Leacock and Chodorow similarity [26] is calculated as follows:

\[
Sim_{LC} = - \log \frac{\text{length}(s_1, s_2)}{2D} 
\]  

(5)

where \( \text{length} \) denotes the shortest path length, and \( D \) is the maximum taxonomy depth.

Resnik similarity [27] measures the similarity between two words based on the information content (IC) of the LCS as:

\[
Sim_{Res} = IC(lcs(s_1, s_2)) 
\]  

(6)

where:

\[
IC(s) = - \log P(s),
\]

Here, \( P(s) \) denotes the probability of encountering an instance of a word, \( s \), in a large corpus.

Jiang and Conrath similarity [28] measures how similar two-word senses are based on the IC of the LCS and that of the two input synsets as:

\[
Sim_{JC} = \frac{1}{IC(s_1) + IC(s_2) - 2 \times IC(lcs(s_1, s_2))} 
\]  

(7)

Lin similarity [29] is similar to the Jiang and Conrath similarity but replaces the negative term of the denominator with the numerator and is formulated as:

\[
Sim_{Lin} = \frac{2 \times IC(lcs(s_1, s_2))}{IC(s_1) + IC(s_2)} 
\]  

(8)

The Leacock and Chodorow similarity only considers the shortest path length between two words. However, the common subsumer might be more rational to measure the similarity between two words. For example, people and whales show a long path length...
but short common subsumer, i.e., mammals, to indicate they are closer by using the common subsumer measures. Hence, the Wu and Palmer similarity considers the LCS to measure the similarity between two words. Furthermore, other measures transfer the result of the LCS into the probability by using the concept of IC. However, these LCS similarities can be considered as the specific monotonic transformation between each other.

However, the above word similarity measures are used for two single words. In practice, the word similarity should consider compound words. Hence, Mihalcea et al. [30] extended the above measures to calculate the similarity between words or compound words used in this paper.

After calculating the similarity between words or compound words, we then use the factor analysis to derive factors composed by the distinct criteria. Note that we can use some orthogonal rotation methods of the factor analysis, e.g., varimax, quartimax, and equamax. This paper will use varimax because it is by far the most popular orthogonal rotation in many software packages and is an incremental improvement upon other methods [31]. All factors are independent of each other, and each factor is represented by an equation composed of distinct criteria. For example, if Factor 1 is composed of the Criteria 1 to 3, the equation can be represented as:

\[ \text{Factor 1} = a_1 \text{Criterion}_1 + a_2 \text{Criterion}_2 + a_3 \text{Criterion}_3 \]  

where \( a \) denotes the factor loading. The conventional AHP can derive the weights of criteria. That is, we will quantify the pairwise comparison matrix of criteria and use the eigenvalue method to obtain the weights of criteria and the corresponding CI and CR values. Once we obtain the information about the weights of Criteria 1 to 3, we can use Equation (9) to derive the weight of Factor 1.

With regard to evaluating alternatives, we can ask the responder to give the scores with respect to the factors, or we can give the pairwise comparison matrix of alternatives with respect to the factors to derive the corresponding scores of alternatives. The process of the proposed method can be depicted as shown in Figure 5.

The hierarchical structure of the method can be represented as shown in Figure 6. The first level is the goal of the problem. The second level is the considered criteria of the goal. The third level indicates the factors which are determined by the result of the factor loading. The last level is the candidate alternatives which are affected by the factors.

Next, we will consider a case study to illustrate the proposed method and compare the result with the conventional AHP.
where $a$ denotes the factor loading. The conventional AHP can derive the weights of criteria. That is, we will quantify the pairwise comparison matrix of criteria and use the eigenvalue method to obtain the weights of criteria and the corresponding CI and CR values. Once we obtain the information about the weights of Criteria 1 to 3, we can use Equation (9) to derive the weight of Factor 1.

With regard to evaluating alternatives, we can ask the responder to give the scores with respect to the factors, or we can give the pairwise comparison matrix of alternatives with respect to the factors to derive the corresponding scores of alternatives. The process of the proposed method can be depicted as shown in Figure 5.

Figure 5. Process of the proposed method.

The hierarchical structure of the method can be represented as shown in Figure 6. The first level is the goal of the problem. The second level is the considered criteria of the goal. The third level indicates the factors which are determined by the result of the factor loading. The last level is the candidate alternatives which are affected by the factors.

Figure 6. The revised framework of the AHP.

Next, we will consider a case study to illustrate the proposed method and compare the result with the conventional AHP.

4. Case Study: Online Shopping

Let us consider customer satisfaction of online shopping reported in Guo et al. [32] as shown in Figure 7. Eight criteria are considered as the essential elements to affect customer satisfaction: web design (WD), security, information quality (IQ), payment method (PM), service quality (SQ), product quality (PQ), product variety (PV), and delivery service (DS). Hence, it is critical to optimize the allocation of resources to achieve maximum customer satisfaction.

Here, we hope to derive the weights of the criteria of online shopping using the AHP. However, this is impossible because these criteria are neither independent, e.g., product quality and product variety, nor have any information about the interdependence between criteria. Hence, we use the proposed method to handle the above problem.
4. Case Study: Online Shopping

Let us consider customer satisfaction of online shopping reported in Guo et al. [32] as shown in Figure 7. Eight criteria are considered as the essential elements to affect customer satisfaction: web design (WD), security, information quality (IQ), payment method (PM), service quality (SQ), product quality (PQ), product variety (PV), and delivery service (DS). Hence, it is critical to optimize the allocation of resources to achieve maximum customer satisfaction.

![Figure 7. Criteria of customer satisfaction in online shopping.](image)

Here, we hope to derive the weights of the criteria of online shopping using the AHP. However, this is impossible because these criteria are neither independent, e.g., product quality and product variety, nor have any information about the interdependence between criteria. Hence, we use the proposed method to handle the above problem.

First, we calculate the criteria similarity matrix based on the synset structure from WordNet [30] as follows:

|                | Web Design | Security | Information Quality | Payment Method | Service Quality | Product Quality | Product Variety | Delivery Service |
|----------------|------------|----------|---------------------|----------------|-----------------|-----------------|-----------------|------------------|
| Web Design     | 1          | 0.172    | 0.085               | 0.156          | 0.183           | 0.183           | 0.200           | 0.172            |
| Security       | 0.172      | 1        | 0.085               | 0.151          | 0.146           | 0.155           | 0.134           | 0.125            |
| Information Quality | 0.085     | 0.085    | 1                   | 0.064          | 0.750           | 0.750           | 0.175           | 0.125            |
| Payment Method | 0.156      | 0.151    | 0.064               | 1              | 0.189           | 0.118           | 0.127           | 0.225            |
| Service Quality | 0.183     | 0.146    | 0.750               | 0.189          | 1               | 0.786           | 0.241           | 0.792            |
| Product Quality | 0.183     | 0.155    | 0.750               | 0.118          | 0.786           | 1               | 0.833           | 0.189            |
| Product Variety | 0.200     | 0.134    | 0.175               | 0.127          | 0.241           | 0.833           | 1               | 0.155            |
| Delivery Service | 0.172     | 0.125    | 0.129               | 0.225          | 0.792           | 0.189           | 0.155           | 1                |

The result of the criteria similarity shows the reason the conventional AHP is inappropriate. For example, the correlation between product quality and service quality is 0.789, and product quality and product variety are 0.833. In fact, all criteria show different degrees of correlation between each other, and the results justify why the proposed method is needed.

Next, we use the above correlation matrix to process the factor analysis and select three factors based on the criterion that the eigenvalue is more significant than one, as shown in Table 3.
**Table 3. Initial explained variance (eigenvalues).**

| Criteria     | Factor 1 | Factor 2 | Factor 3 | Factor 4 | Factor 5 | Factor 6 | Factor 7 | Factor 8 |
|--------------|----------|----------|----------|----------|----------|----------|----------|----------|
| Eigenvalue   | 3.201    | 1.285    | 1.179    | 0.864    | 0.828    | 0.750    | 0.035    | -0.147   |
| Variance %   | 40.018   | 16.038   | 14.742   | 10.802   | 10.354   | 9.441    | 0.439    | 0.036    |
| Cumulation % | 40.018   | 56.056   | 70.798   | 81.600   | 91.954   | 101.394  | 101.834  | 100.000  |

Then, we use the orthogonal varimax rotation to calculate the factor loading of the criteria with respect to the extracted factors, as shown in Table 4.

**Table 4. Factor loadings of the criteria with respect to the three factors.**

| Criteria       | Factor 1 | Factor 2 | Factor 3 |
|----------------|----------|----------|----------|
| web design     | 0.147    | 0.039    | 0.644 *  |
| security       | 0.102    | 0.022    | 0.607 *  |
| information quality | 0.665 * | 0.509    | -0.196   |
| payment method | -0.062   | 0.250    | 0.600 *  |
| service quality | 0.480   | 0.895 *  | 0.080    |
| product quality | 0.976*  | 0.282    | 0.109    |
| product variety | 0.806 * | -0.141   | 0.348    |
| delivery service | -0.049 | 0.848 *  | 0.296    |

* indicates the maximum loadings with respect to the factors.

Table 4 indicates the three factors’ compositions: information quality, product quality, and product variety belong to Factor 1; service quality and delivery service belong to Factor 2; and web design, security, and payment method belong to Factor 3. As shown in Figure 8, the hierarchical clustering result also indicates the same result as that of the factor analysis.

![Hierarchical clustering of the correlation matrix.](image)

**Figure 8. Hierarchical clustering of the correlation matrix.**

Therefore, we can derive the three-factor equations with respect to the criteria as follows:

- Factor 1 = 0.665 × information quality + 0.976 × product quality + 0.806 × product variety
- Factor 2 = 0.895 × service quality + 0.848 × delivery service
- Factor 3 = 0.644 × web design + 0.607 × security + 0.600 × payment method

The factor equations explain that three independent factors affect the result of customer satisfaction in online shopping and the relationship with respect to their own distinct criteria. Hence, if we can derive the criteria weights, we can obtain the factors’ weights and conclude the customer satisfaction problem. The weights of the criteria can be derived by using the conventional AHP, and the pairwise comparison matrix is given as follows:
Note that $\lambda_{\text{max}} = 8.811$, CI = 0.011, and CR = 0.083.

Next, we can depict the factor weight figure, as shown in Figure 9, to present the criteria and factors' weights and the factor loadings.

![Figure 9. Deriving weights of factors by criteria.](image)

We can tabulate the result in Figure 9 as shown in Table 5:

**Table 5.** The comparison between the AHP and the proposed method.

| Criteria | Product Variety | Information Quality | Product Quality | Delivery Service | Service Quality | Payment Method | Web Design | Security |
|----------|-----------------|---------------------|-----------------|------------------|----------------|----------------|-----------|----------|
| AHP Weights | 0.2207 | 0.1747 | 0.0620 | 0.3450 | 0.1032 | 0.0193 | 0.0412 | 0.0338 |
| Factors | Factor 1 | Factor 2 | Factor 3 |
| Our Weights | 0.443 | 0.4823 | 0.0735 |
Note that the normalized factor weights might have a reversal rank with respect to the composited criterion weights. For example, the summation of the weights of the product variety, information quality, and product quality is equal to 0.4574, but the normalized weight of Factor 1 is 0.4443, i.e., ranked from the first to the second of the three factors. These differences might result in different decision-making for the problem. Next, we consider further discussion based on the results above.

5. Discussions

The AHP is a famous approach in multi-criteria decision-making to derive the weights of criteria due to its simplicity and rationality. Although many sophisticated approaches have been proposed to improve the problems of the AHP, it is without a doubt still one of the most popular methods. The primary concept of the AHP is to derive the weights of criteria through the pairwise comparison matrix under the assumption of a hierarchical structure, i.e., properties of the independent criteria. However, the assumption is one of the critical problems of the AHP and is reviewed in this paper.

The major distinction of the paper is that we revise the conventional AHP by incorporating the criteria similarity and explorative factor analysis. The criteria similarity is calculated via the WordNet database. Hence, we do not need extra costs or questionnaires to obtain the needed information. Then, we can use the explorative factor analysis to derive the independent factors from the correlated criteria. Finally, we can use the results of the AHP for the correlated criteria and factor loadings to calculate the weights of factors. Hence, the evaluation of alternatives will depend on the factors’ weights rather than the correlated criteria.

We used an online shopping case to illustrate the proposed method and showed the difference from the conventional AHP. We concluded the three independent factors, which were composed of eight correlated criteria. Then, we derived the factor loadings and the weights of the criteria from calculating the factors’ weights. Compared with the conventional AHP, it only considers the weights of criteria. Hence, the possible difference between the conventional AHP and the proposed method to determine the best alternative is clear. The limitation of the method is that we assume that all (compound) words are listed in WordNet; otherwise, the similarity between words cannot be calculated. Although the WordNet database contains 117,000 synsets, it is not a surprise that some professional words are not listed in the synsets. Further study could consider a more complicated hierarchical structure with correlated criteria to test the proposed method.

6. Conclusions

In this paper, the independence of criteria of the AHP is reviewed by accounting for the correlation effect between criteria. The major advantage of the proposed method is two-fold. One is to maintain simplicity, as in the AHP. The other is to account for the correlation effect between criteria. Hence, we do not need a further complicated method, e.g., ANP, to increase the amount of work much to gather more information. In addition, the result of the case study showed the significant difference between the proposed method and the conventional AHP. We believe that the proposed method has the more rational and correct result in determining the best alternative.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The author declares no conflict of interest.
References

1. Saaty, R.M. The analytic hierarchy process—What it is and how it is used. *Math. Model.* 1987, 9, 161–176. [CrossRef]
2. Saaty, T.L. How to make a decision: The analytic hierarchy process. *Eur. J. Oper. Res.* 1990, 48, 9–26. [CrossRef]
3. Saaty, T.L. *Decision Making with Dependence and Feedback: The Analytic Network Process*; RWS Publications: Pennsylvania, PA, USA, 1996; ISBN 0-9620317-9-8.
4. Darko, A.; Chan, A.P.C.; Ameyaw, E.E.; Owusu, E.K.; Pärn, E.; Edwards, D.J. Review of application of analytic hierarchy process (AHP) in construction. *Int. J. Constr. Manag.* 2019, 19, 436–452. [CrossRef]
5. Kubler, S.; Robert, J.; Neumaier, S.; Umbrich, J.; Le Traon, Y. Comparison of metadata quality in open data portals using the Analytic Hierarchy Process. *Gov. Inf. Q.* 2018, 35, 13–29. [CrossRef]
6. dos Santos, P.H.; Neves, S.M.; Sant’Anna, D.O.; de Oliveira, C.H.; Carvalho, H.D. The analytic hierarchy process supporting decision making for sustainable development: An overview of applications. *J. Clean. Prod.* 2019, 212, 119–138. [CrossRef]
7. Kubler, S.; Robert, J.; Derigent, W.; Voisin, A.; Le Traon, Y. A state-of-the-art survey & testbed of fuzzy AHP (FAHP) applications. *Expert Syst. Appl.* 2016, 65, 398–422. [CrossRef]
8. Zhú, K. Fuzzy analytic hierarchy process: Fallacy of the popular methods. *Eur. J. Oper. Res.* 2014, 236, 209–217. [CrossRef]
9. Sahoo, S.; Dhar, A.; Kar, A. Environmental vulnerability assessment using Grey Analytic Hierarchy Process based model. *Environ. Impact Assess. Rev.* 2016, 56, 145–154. [CrossRef]
10. Aguaron, J.; Escobar, M.T.; Moreno-Jimenez, J.M.; Turon, A. AHP-Group Decision Making Based on Consistency. *Mathematics* 2019, 7, 242. [CrossRef]
11. Samanlioglu, F.; Ayaga, Z. A fuzzy AHP-PROMETHEE II approach for evaluation of solar power plant location alternatives in Turkey. *J. Intell. Fuzzy Syst.* 2017, 33, 859–871. [CrossRef]
12. Tušjak-Suban, D.; Bajec, P. Integration of AHP and GTMA to Make a Reliable Decision in Complex Decision-Making Problems: Application of the Logistics Provider Selection Problem as a Case Study. *Symmetry* 2020, 12, 766. [CrossRef]
13. Lokhande, T.; Kote, A.; Mali, S. Integration of GIS and AHP-ANP Modeling for Landfill Site Selection for Nagpur City, India. In *Lecture Notes in Civil Engineering*; Metzler, J.B., Ed.; Springer: Berlin/Heidelberg, Germany, 2020; pp. 499–510.
14. Martin, H.; Koylass, J.; Welch, F. An exploration of the consistency limits of the analytical hierarchy process and its impact on contractor selection. *Int. J. Constr. Manag.* 2016, 18, 14–25. [CrossRef]
15. Whitaker, R. Criticisms of the Analytic Hierarchy Process: Why they often make no sense. *Math. Comput. Model.* 2007, 46, 948–961. [CrossRef]
16. Franke, J.; Kresta, A. Judgment Scales and Consistency Measure in AHP. *Procedia Econ. Finance* 2014, 12, 164–173. [CrossRef]
17. Ji, P.; Jiang, R. Scale transitivity in the AHP. *J. Oper. Res. Soc.* 2003, 54, 896–905. [CrossRef]
18. Bernasconi, M.; Choirat, C.; Seri, R. The Analytic Hierarchy Process and the Theory of Measurement. *Manag. Sci.* 2010, 56, 699–711. [CrossRef]
19. Liu, H.-H.; Yeh, Y.-Y.; Huang, J.-J. Correlated Analytic Hierarchy Process. *Math. Probl. Eng.* 2014, 2014, 1–7. [CrossRef]
20. Keeney, R.L.; Raiffa, H. Decision Analysis with Multiple Conflicting Objectives. *Preferences and Value Tradeoffs*. 1975. Available online: http://pure.iiasa.ac.at/id/eprint/375/ (accessed on 13 March 2021).
21. Saaty, T.L. A scaling method for priorities in hierarchical structures. *J. Math. Psychol.* 1977, 15, 234–281. [CrossRef]
22. Stávková, J.; Stejskal, L.; Toufarová, Z. Factors influencing consumer behaviour. *Agric. Econ. (Zemědělská Ekonomika)* 2008, 54, 276–284. [CrossRef]
23. Xu, Y.; Chong, T.W.; Krilavičius, T.; Man, K.L. Perceived Benefits, Risks and Trust on Online Shopping Festival. In *Communications in Computer and Information Science*; Springer International Publishing: Berlin, Germany, 2015; Volume 538, pp. 225–235.
24. Forsythe, S.; Liu, C.; Shannon, D.; Gardner, L.C. Development of a scale to measure the perceived benefits and risks of online shopping. *J. Interact. Mark.* 2006, 20, 55–75. [CrossRef]
25. Wu, Z.; Palmer, M. Verbs semantics and lexical selection. In *Proceedings of the 32nd Annual Meeting on Association of Computational Linguistics*, Mexico City, Mexico, 27–30 June 1994; pp. 133–138. [CrossRef]
26. Leacock, C.; Martin, C. Combining local context and WordNet similarity for word sense identification. *WorldNet Electron. Lex. Database* 1998, 49, 265–283.
27. Resnik, P. Using information content to evaluate semantic similarity. In *Proceedings of the 14th International Joint Conference on Artificial Intelligence (IJCAI-95)*; Montreal, QC, Canada, 20–25 August 1995; pp. 448–453.
28. Jiang, J.J.; Conrath, D.W. Semantic Similarity Based on Corpus Statistics and Lexical Taxonomy. In *Proceedings of the 10th Research on Computational Linguistics International Conference*, Taipei, Taiwan, 22–24 August 1997; pp. 19–33.
29. Lin, C.-Y.; Hovy, E. Automatic evaluation of summaries using N-gram co-occurrence statistics. In *Proceedings of the 2003 Conference of the North American Chapter of the Association for Computational Linguistics on Human Language Technology* NAAACL ‘03, Stroudsburg, PA, USA, 27 May–1 June 2003; pp. 71–78.
30. Mihalcea, R.; Corley, C.; Strapparava, C. Corpus-based and knowledge-based measures of text semantic similarity. *Aasi* 2006, 6, 775–780.
31. Osborne, J.W. What is Rotating in Exploratory Factor Analysis? *Pract. Assess. Res. Eval.* 2015, 20. [CrossRef]
32. Guo, X.; Ling, K.C.; Liu, M. Evaluating Factors Influencing Consumer Satisfaction towards Online Shopping in China. *Asian Soc. Sci.* 2012, 8, 40. [CrossRef]