A novel hybrid social media platform selection model using fuzzy ANP and COPRAS-G

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Fuzzy set theory
COPRAS-G

ABSTRACT

The growing popularity of social media platforms has sparked new marketing opportunities for companies. Marketers have turned to social media campaigns as a means to build brand loyalty, exposure, and engagement. While social media has evolved into a powerful marketing tool, marketers must carefully choose the most suitable social media platform. Improper selection of the social media platform can be costly and can be detrimental to the brand. Despite all of the supposed benefits, selecting the right social media platform has been a daunting task for corporate marketers. The social media platform selection problems are inherently complex problems with multiple and often conflicting criteria. We propose a novel analytical framework for social media platform selection. The proposed hybrid framework integrates the Analytic Network Process (ANP) with fuzzy set theory and the COMplex PRoportional ASsessment of alternatives with Grey relations (COPRAS-G) method. The ANP and fuzzy set theory are used to determine the importance weight of the social media platform selection criteria in a fuzzy environment. The COPRAS-G method is used to rank and select the most suitable social media platform. A case study is presented to demonstrate the applicability of the proposed framework and exhibit the efficacy of the procedures and algorithms.

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1. Introduction

The World Wide Web, described by Sir Tim Berners-Lee as “an interactive sea of shared knowledge......made of the things we and our friends have seen, heard, believe or have figured out,” has drastically changed traditional marketing (Evans & McKee, 2010, p. xvii). Traditional marketing involves an information exchange in a one-way direction (e.g., television and radio commercials). On the contrary, web-based marketing involves two-way communication with customers while maintaining the push-messaging (Trusov, Bucklin, & Pauwels, 2009). Social media facilitate two-way communication and connect people on a mass scale. The collaborative technologies that now define contemporary marketplaces provide tremendous opportunities for new business initiatives across a wide range of applications. These social media technologies allow savvy businesses to connect with their customers and prosper through a two-way collaborating relationship. Social media sites are leveraging direct selling to reach social networks of family, friends, and co-workers, thus extending the reach of direct selling (Glenn, 2011). Social media comprise both the conduits and the content disseminated through interactions between individuals and organizations (Kietzman, Hermkens, McCarthy, & Silvestre, 2011).

Despite all of the supposed benefits, selecting the right social media platform has been a daunting task for corporate marketers. This difficulty is due to: (i) the optimal frequency of posting; (ii) the fixed cost of establishing a social media presence; (iii) the average cost of creating a typical ‘engagement entry’ (e.g., a Facebook posting, a YouTube video, a tweet, etc.) on a social media site; and (iv) the expected cost of building a reasonable follower audience or fan base. Although the social media platform selection problems are inherently complex problems with multiple and often conflicting criteria, no analytical social media platform evaluation and selection model has been proposed in the literature. Most existing models are limited to simple classification charts categorizing the different types of social media engagements (McEllan, 2010). There is a need for a more systematic and analytical framework for social media platform evaluation and selection.
We propose a novel analytical framework for social media platform selection. The proposed hybrid framework integrates the Analytic Network Process (ANP) with fuzzy set theory and the Complex Proportional Assessment of alternatives with Grey relations (COPRAS-G) method. The ANP and fuzzy set theory are used to determine the importance weight of the social media platform selection criteria in a fuzzy environment. The COPRAS-G method is used to rank and select the most suitable social media platform.

The remainder of this paper is organized as follows. In Section 2 we review the relevant literature on social media marketing, Multi-Attribute Decision Making (MADM) and the Analytic Network Process (ANP), fuzzy set theory and the Complex Proportional Assessment of alternatives with Grey relations (COPRAS-G) method. In Section 3 we provide the details of the hybrid method proposed in this study. In Section 4 we present a real-world case study to demonstrate the applicability of the proposed framework and exhibit the efficacy of the procedures and algorithms. In Section 5 we present our conclusions and future research directions.

2. Literature review

Social media are Internet platforms used to disseminate information through social interactions that provide decentralized user level content and public membership (Abrahams, Jiao, Wang, & Fan, 2012). Most social media are highly accessible and scalable and allow for a variety of social interactions such as social viral activity and intimate community engagement (Li & Shiu, 2012). The most widely used social media mechanisms are online forums such as product or service review websites, blogs, chat rooms, discussion boards, and social networking websites like Facebook, Twitter, LinkedIn, Google+, and YouTube (Kaplan & Haenlein, 2010; Mangold & Faulds, 2009). Social media marketing addresses people as part of a social network and uses social relations and social influences between people to sell products or services (Wang, Wang, & Farn, 2009).

Five distinct properties make social media a powerful marketing tool: (1) participation: social media encourages contributions and feedback (Durugbo, 2012); (2) openness: most social media services are open to feedback and participation by encouraging voting, commenting and the sharing of information (Bertot, Jaeger, & Grimes, 2010); (3) conversation: traditional media is about one-way communication and use of links to other sites, resources and social viral information is known and part of the information is unknown. Since

...
uncertainty always exists, one is always somewhere in the middle, somewhere between the back and white extremes (i.e., somewhere in the grey area).


3. The proposed hybrid method

The hybrid model depicted in Fig. 1 integrates the ANP method with fuzzy set theory and the COPRAS-G method to assess the alternative social media markets.

3.1. The ANP method

The ANP method (Saaty, 2001) is comprised of the following four steps:

3.1.1. Step 1: Form the network structure

In the first step, the criteria, the sub-criteria and the alternatives are identified. Then, the clusters of the elements are determined and a network is formed based on the relationship among the clusters and within the elements in each cluster. Several different relationships could be found in a network. Direct relationship is a regular dependency in a standard hierarchy. Indirect relationship is a relationship that flows through another criteria or alternative. The direct relationship between a criterion and itself is characterized by “self-interacting” criteria. Finally, interdependencies are relationships among criteria which form a mutual effect.

3.1.2. Step 2: Form the pairwise comparison matrices

In the second step, pairwise comparisons are performed on the elements within the clusters as they influence each cluster and on those that it influences, with respect to that criterion. The pairwise comparisons are made with respect to a criterion or sub-criterion of the control hierarchy. Thus, the importance weights of the factors are determined. In pairwise comparison, decision makers compare two elements. Then, they determine the contribution of the factors to the result (Saaty, 2001). In ANP, similar to AHP, pairwise comparison matrices are formed using the 1–9 scale of relative importance proposed by Saaty (1996). The values of the pairwise comparisons are assigned to a comparison matrix and a local priority vector is obtained from the eigenvector which is calculated as follows:

\[ A w = \lambda_{\text{max}} w \]  

(1)

In this equation, \( A \) and \( w \) represent the pairwise comparison matrix, the eigenvector, and the eigenvalue, respectively. Saaty and Takizawa (1986) has proposed a normalization algorithm for the approximate solution of \( w \) (Saaty & Takizawa, 1986). The matrix which shows the comparison between the factors is obtained as follows:

\[ A = [a_{ij}]_{n \times n}; \quad i = \frac{1}{n}; \quad j = \frac{1}{n} \]  

(2)

3.1.3. Step 3: Obtain the priority vector

The significance distribution of the factors as a percentage is obtained as follows:

\[ B_i = |b_{ij}|_{n \times n}; \quad i = \frac{1}{n}; \frac{1}{n} \]  

(3)

\[ b_j = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \]  

(4)

\[ C = |b_{ij}|_{n \times n}; \quad i = \frac{1}{n}; \quad j = \frac{1}{n} \]  

(5)

\[ w_i = \frac{\sum_{j=1}^{n} c_{ij}}{n} W = [w_i]_{n \times 1} \]  

(6)
3.1.4. Step 4: Form the super-matrix and limit super-matrix

The overall structure of the super-matrix is similar to the Markov chain process (Saaty, 1996, 2005). To obtain the global priority in a system that has interdependent effects, all local priority vectors are allocated to the relevant columns of the super-matrix. Consequently, the super-matrix is a limited matrix and every part of it shows the relationship between two elements in the system. The long-term relative impacts of the elements to each other are obtained by raising the super-matrix to a power. To equalize the importance weights, the matrix is raised to the \((2k + 1)\)th power, where \(k\) is an arbitrary large number (Saaty, 2001). As noted by Lee, Kim, Cho, and Park (2009, p. 897) “Raising the weighted super-matrix to the power \(2k + 1\), where \(k\) is an arbitrarily large number, allow convergence of the matrix, which means the row values converge to the same value for each column of the matrix.”

The new matrix is called the limited Super-matrix (Saaty, 1996). The consistency of the pairwise comparison matrix is checked with the consistency index (CI). For accepted consistency, CI must be smaller than 0.10 (Saaty & Takizawa, 1986).

3.2. The fuzzy method

Let the universe of discourse \(X\) be the subset of real numbers \(R\). The fuzzy number \(M\) on \(R\) is a triangular fuzzy number if its membership function \(\mu_M(x): R \rightarrow [0, 1]\) is equal to:

\[
\mu_M(x) = \begin{cases} 
\frac{x-a}{b-a}, & x \in [a, b] \\
\frac{c-x}{c-b}, & x \in [b, c] \\
0, & \text{otherwise}
\end{cases}
\]  

(7)

where \(a \leq b \leq c\), and \(a\) and \(c\) are the lower and upper bound values of the support of \(M\), respectively; and \(b\) is the peak or center. The triangular number is denoted by \((a, b, c)\). If \(a = b = c\), the number is an ordinary (non-fuzzy) number. The support of the matrix is the set \(\{x \in R | a < x < c\}\).

Consider two triangular fuzzy numbers \(M_1 = (a_1, b_1, c_1)\) and \(M_2 = (a_2, b_2, c_2)\). The following describes the addition and inverse of the two fuzzy numbers \(M_1\) and \(M_2\), respectively:

\[
(a_1, b_1, c_1) \oplus (a_2, b_2, c_2) = (a_1 + a_2, b_1 + b_2, c_1 + c_2)
\]  

(8)

\[
(a_1, b_1, c_1) \ominus (a_2, b_2, c_2) = (a_1a_2 + b_2b_2 + c_1c_2)
\]  

(9)

\[
(a_1, b_1, c_1)^{-1} \approx \left( \frac{1}{c_1}, \frac{1}{b_1}, \frac{1}{a_1} \right)
\]  

(10)

The triangular fuzzy numbers used in this model are suggested by Önüt, Karar, and Tugba (2008) to represent the subjective pair-wise comparisons of the experts’ judgments. Table 1 presents the triangular fuzzy scale used to convert the linguistic values into fuzzy scales.

We use the extent analysis method proposed by Chang (1996) to consider the extent to which an object can satisfy the goal (or the satisfaction extent). In this method, the extent is quantified with a fuzzy number. Based on the fuzzy values for the extent analysis of each object, a fuzzy synthetic degree value is obtained using the following two steps:

3.2.1. Step 1: Define the value of the fuzzy synthetic extent

The value of the fuzzy synthetic extent is defined using the standard fuzzy arithmetic as follows:

\[
S_i = \sum_{j=1}^{m} M_i^j \odot \left( \sum_{j=1}^{m} M_i^j \right)^{-1}
\]  

(11)

where \(S_i\) is the fuzzy extent value and \(\odot\) is defined as the multiplication fuzzy operation. \(M_i^j\) is a triangular fuzzy number representing the extent analysis value of the decision element \(i\) with respect to the goal \(j\). \(M_i^j\) is the generic element of the fuzzy pair-wise comparison matrix. To obtain \(\sum_{j=1}^{m} M_i^j\), we perform the fuzzy addition operation of \(m\) extent analysis values for a particular matrix as follows:

\[
\sum_{j=1}^{m} M_i^j = \left( \sum_{j=1}^{m} a_i, \sum_{j=1}^{m} b_i, \sum_{j=1}^{m} c_i \right)
\]  

(12)

In order to obtain \(\left( \sum_{j=1}^{m} a_i, \sum_{j=1}^{m} b_i, \sum_{j=1}^{m} c_i \right)^{-1}\), we perform the fuzzy addition operation on \(M_i^j(i = 1, 2, \ldots, m)\) values as follows:

\[
\left( \sum_{j=1}^{m} M_i^j \right)^{-1} = \left( \frac{1}{\sum_{j=1}^{m} a_i}, \frac{1}{\sum_{j=1}^{m} b_i}, \frac{1}{\sum_{j=1}^{m} c_i} \right)
\]  

(13)

We then compute the inverse of the vector as follows:

\[
\left( \sum_{j=1}^{m} M_i^j \right)^{-1} \odot \left( \sum_{j=1}^{m} M_i^j \right)^{-1} = \left( \frac{1}{\sum_{j=1}^{m} a_i}, \frac{1}{\sum_{j=1}^{m} b_i}, \frac{1}{\sum_{j=1}^{m} c_i} \right)
\]  

(14)

3.2.2. Step 2: Define the degree of possibility

The degree of possibility of \(M_2 = (a_2, b_2, c_2) \geq M_1 = (a_1, b_1, c_1)\) is defined as:

\[
V(M_2 \geq M_1) = \sup_{x \in R} \min(\mu_{M_1}(x), \mu_{M_2}(y))
\]  

(15)

and can be equivalently expressed as follows:

\[
V(M_2 \geq M_1) = \text{hgt}(M_1 \cap M_2) = \mu_{M_2}(d)
\]  

(16)

where \(d\) is the ordinate of the highest intersection point \(D\) between \(\mu_{M_1}\) and \(\mu_{M_2}\). To compare \(M_1\) and \(M_2\), we need both the values of \(V(M_1 \geq M_2)\) and \(V(M_2 \geq M_1)\) given in Fig. 2.

The degree of possibility for a convex fuzzy number to be greater than \(k\) convex fuzzy numbers \(M_i(i = 1, 2, \ldots, k)\) can be defined by:

\[
V(M \geq M_1, M_2, \ldots, M_k) = \min \{V(M \geq M_1), (M \geq M_2), \ldots, (M \geq M_k)\} = \min V(M \geq M_i)
\]  

(17)

where \(i = 1, 2, \ldots, k\). Assume that:

\[
d'(A_i) = \min V(M \geq M_i)
\]  

(18)

Table 1

<table>
<thead>
<tr>
<th>Linguistic scale for importance</th>
<th>Triangular fuzzy scale ((a,b,c))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Just equal</td>
<td>((1.0, 1.0, 1.0))</td>
</tr>
<tr>
<td>Equal importance</td>
<td>((1.0, 0.3, 0.3))</td>
</tr>
<tr>
<td>Weak importance of one over another</td>
<td>((1.0, 0.3, 0.5))</td>
</tr>
<tr>
<td>Essential or strong importance</td>
<td>((3.0, 0.5, 0.7))</td>
</tr>
<tr>
<td>Very strong importance</td>
<td>((5.0, 0.7, 0.9))</td>
</tr>
<tr>
<td>Extremely preferred</td>
<td>((7.0, 0.9, 0.9))</td>
</tr>
</tbody>
</table>

If factor \(i\) has one of the above numbers assigned to it when compared to factor \(j\), then \(j\) has the reciprocal value when compared with \(i\): \(M_i^{-1} = \left( \frac{1}{a_i}, \frac{1}{b_i}, \frac{1}{c_i} \right)\)
where $k = 1, 2, ..., n; k \neq i$. Then, the weight vector is given by:
\[
W' = (d(A_1), d(A_2), \ldots, d(A_n))^T
\]  

(19)

where $A_i (i = 1, 2, ..., n)$ are $n$ decision elements. The normalized weight vectors are:
\[
W = (d(A_1), d(A_2), \ldots, d(A_n))^T
\]

(20)

where $W$ is a non-fuzzy number.

3.3. The COPRAS-G method

We use the COPRAS-G method proposed by Zavadskas et al. (2009) to calculate the utility degree and priority order of the alternative social media markets. This method works on a stepwise ranking and evaluation procedure of the alternatives in terms of their significance and utility degree as follows:

3.3.1. Step 1: Identify the relevant criteria

We first identify the criteria relevant to the social media platform selection problem.

3.3.2. Step 2: Construct the decision matrix

We then construct the decision matrix $X$ as follows:
\[
\otimes X = \begin{bmatrix}
[\otimes x_{11}] & [\otimes x_{12}] & \ldots & [\otimes x_{1m}]
\end{bmatrix}
\]

\[
= \begin{bmatrix}
[\otimes x_{21}] & [\otimes x_{22}] & \ldots & [\otimes x_{2m}]
\end{bmatrix}
\]

\[
= \begin{bmatrix}
[\otimes x_{n1}] & [\otimes x_{n2}] & \ldots & [\otimes x_{nm}]
\end{bmatrix}
\]

where $\otimes x_{ji}$ is determined by $x_{ji}$ (the smallest value, i.e., the lower limit) and $x_{ji}$ (the biggest value, i.e., the upper limit).

3.3.3. Step 3: Determine the importance weight of each criterion

We then determine the importance weight of each criterion $(q_i)$ by using the ANP.

3.3.4. Step 4: Calculate the weighted normalized decision matrix

In this step we first normalize the decision-making matrix $X$ in order to determine the importance weight of the selection criteria:
\[
\delta y_i = \frac{x_{ji} - 2x_{ji}}{\frac{1}{2} \left( \sum_{j=1}^{n} x_{j1} + \sum_{j=1}^{n} x_{j2} \right) - \frac{1}{2} \left( \sum_{j=1}^{n} x_{j1} + \sum_{j=1}^{n} x_{j2} \right) - \frac{1}{2} \left( \sum_{j=1}^{n} x_{j1} + \sum_{j=1}^{n} x_{j2} \right) + 1}
\]

\[
\hat{x}_{ji} = \frac{\delta y_i}{\frac{1}{2} \left( \sum_{j=1}^{n} \delta y_i + \sum_{j=1}^{n} \delta y_i \right) + \sum_{j=1}^{n} \delta y_i - 1}
\]

(22)

where $x_{ji}$ is the lowest value of criterion $i$ for alternative $j$; $y_i$ is the highest value of criterion $i$ for alternative $j$; $m$ is the number of criteria; and $n$ is the number of alternatives under consideration. The normalization process results in the following normalized decision matrix:

\[
\otimes X = \begin{bmatrix}
[\otimes x_{11}] & [\otimes x_{12}] & \ldots & [\otimes x_{1m}]
\end{bmatrix}
\]

\[
= \begin{bmatrix}
[\otimes x_{21}] & [\otimes x_{22}] & \ldots & [\otimes x_{2m}]
\end{bmatrix}
\]

\[
= \begin{bmatrix}
[\otimes x_{n1}] & [\otimes x_{n2}] & \ldots & [\otimes x_{nm}]
\end{bmatrix}
\]

In order to construct the weighted normalized decision matrix, we first calculate the weighted normalized values $\otimes x_{ji}$ as follows:
\[
\otimes x_{ji} = \otimes x_{ji} - q_i \text{ or } \otimes x_{ji} = \tilde{x}_{ji} - q_i
\]

(23)

where $q_i$ is the relative importance of the $i$th criterion determined by using the ANP.

We then construct the weighted normalized decision matrix $\otimes X$ as follows:
\[
\otimes X = \begin{bmatrix}
[\otimes x_{11}] & [\otimes x_{12}] & \ldots & [\otimes x_{1m}]
\end{bmatrix}
\]

\[
= \begin{bmatrix}
[\otimes x_{21}] & [\otimes x_{22}] & \ldots & [\otimes x_{2m}]
\end{bmatrix}
\]

\[
= \begin{bmatrix}
[\otimes x_{n1}] & [\otimes x_{n2}] & \ldots & [\otimes x_{nm}]
\end{bmatrix}
\]

(24)

3.3.5. Step 5: Determine the relative significance of each alternative

We first calculate the sums $P_j$ of the criterion values (whose larger values are more preferable) as follows:
\[
P_j = \frac{1}{2} \sum_{i=1}^{m} (\tilde{x}_{ji} + \tilde{x}_{ji})
\]

(25)

We then calculate the sums $R_j$ of the criterion values (whose smaller values are more preferable) as follows:
\[
R_j = \frac{1}{2} \sum_{i=k+1}^{m} (\tilde{x}_{ji} + \tilde{x}_{ji})
\]

(26)

where $(m - k)$ is the number of criteria which must be minimized.

We then determine the minimum value of $R_j$ as follows:
\[
R_{min} = \min_j R_j ; j = 1, \ldots, n
\]

(27)

The relative significance of each alternative is then calculated as follows:
\[
Q_j = P_j + \frac{\sum_{j=1}^{m} R_j}{R_{min}}
\]

(28)

3.3.6. Step 6: Calculate the utility degree of each alternative

In order to calculate the utility degree of each alternative, we first determine the optimally criterion $K$ as follows:
\[
K = \max_j Q_j ; j = 1, \ldots, n
\]

(29)

The degree of project utility is determined by comparing the alternatives under consideration with the best alternative. The values of the utility degree range from 0% (for the worst alternative) to 100% (for the best alternative). The utility degree of each alternative $j$ is calculated as follows:
\[
N_j = \frac{Q_j}{Q_{max}} \times 100\%
\]

(30)

where $Q_j$ and $Q_{max}$ are the significances of the alternatives obtained from Eq. (29).
4. Case study

This study was conducted for one of the largest airlines in the Middle East, Trans-Gulf Airline, which was considering social marketing to convert “likes” into paying customers. Part of their marketing strategy was to choose the best social media platform money could buy. While social media may have a low financial cost, it can take a tremendous amount of time, an asset that’s often scarce in many organizations. The main financial costs of social media marketing are content production and editing, strategy execution, and impact analysis among others. To achieve this goal, Trans-Gulf was considering five social media platforms including: Facebook (A1), Twitter (A2), LinkedIn (A3), Google + (A4), and YouTube (A5). A team of five marketing managers at Trans-Gulf participated in the evaluation process. The team carefully reviewed a large number of social marketing platform assessment criteria. After several rounds of brainstorming sessions, the assessment team at Trans-Gulf selected the five criteria presented in Table 2 to evaluate these five social media platforms.

The content score is a subjective score, used to capture the amount of relevant information provided by a social media site. Visitors to a website scan content and often decide within a few seconds if they want to read more or switch over to another site. The impression score is a subjective score used to capture this behavior. Cost is a subjective score used to estimate the financial costs of a social media marketing including content production and editing, strategy execution, and impact analysis. Some social media websites are very basic and some are pretty sophisticated in design and layout. The look and feel score is a subjective score used to measure the look and feel of a social media site in terms of user friendliness and design. Finally, the audience fit is a subjective score given to a social media website in terms of the educational level and age of its visitors. The linguistic variables that were used by the marketing managers were expressed in positive triangular fuzzy numbers for each criterion. The linguistic variables matching the triangular fuzzy numbers and the corresponding membership functions were provided earlier in Table 1. We employed a Likert Scale of fuzzy numbers starting from 1 to 9. The fuzzy comparison scale with respect to the linguistic variables that describes the importance of criteria was also provided earlier in Table 1. The team studied the criteria and sub-criteria presented in Table 2 and determined a maximizing optimization direction for factors \(x_1, x_2, x_{4.1}, x_{4.2}, x_{5.1}, x_{5.2}\) and a minimization optimization direction for factor \(x_3\). The team also studied the relationship and interrelationships among the criteria and sub-criteria and developed the network diagram presented in Fig. 3.

The relationships presented in Fig. 3 were used to make pairwise comparisons among the criteria. Using the extent analysis method proposed by Chang (1996), the team considered the extent to which a criterion (or sub-criterion) could satisfy the overall social marketing goal. The triangular fuzzy scale presented in Table 1 was used to quantify the fuzzy numbers. In Table 3 we present an example pairwise comparison matrix for the “Look & Feel” \(x_4\).

We used Eqs. (11)–(20) to define the values of the fuzzy synthetic extents and the degrees of possibilities. As an example, the values of the fuzzy synthetic extents for the “Look & Feel” criteria are calculated as follows:

\[
S_{x_4} = (0.0209, 0.0337, 0.0564) \odot (5.5709, 9.9816, 16.0094) \\
= (0.1162, 0.3392, 0.9032)
\]

The minimum the degrees of possibility is calculated as follows:

\[
\text{Min } V(S_{x_1} \geq S_{x_2}) = 0.8200
\]

Similar calculations performed on the remaining criteria and sub-criteria produced the following weight vector:

\[
W^* = (1.0000, 0.8200, 0.5647, 0.5082, 0.6983)^T
\]

The following normalized weights are calculated by dividing each weight into the total weight:

\[
W = (0.2785, 0.2283, 0.1572, 0.1415, 0.1944)
\]

where \(W\) is a non-fuzzy number.

In Table 4 we present an example of a pairwise comparison matrix for the elements of “Audience Fit” \(x_{5.1}\) and \(x_{5.2}\) on the design component of the “Look & Feel” cluster calculated using Eq. (11)–(20).

After all comparisons and weighting processes were completed, we obtained the overall priority weights of the criteria and sub-criteria shown in the initial matrix presented in Table 5.

In order to find the weighted super matrix, we first had to normalize and cluster the initial matrix presented in Table 5. The clustering and normalization process resulted in the weighted super matrix presented in Table 6.

We then constructed the limit super matrix presented in Table 7 by finding the power of the weighted super matrix according to Markov’s Eq. (32). According to the ANP, the power calculation process is completed when the consecutive powers become equal.

The limit super matrix is calculated as:

\[
\lim_{k \to \infty} W^k = \frac{W^*}{1 - W^*} = (1.4151, 1.0000, 0.6983, 0.5082, 0.2785)
\]

The criteria and sub-criteria values shown in the rows of the limit super matrix were used in the COPRAS-G method. As shown in Table 7, the “Content” criterion \(x_{1.1}\) was the most important criterion for selecting the most suitable social media platform.

Next, the COPRAS-G method and the importance weights found with the fuzzy ANP method were used to evaluate the five social media platforms of Facebook (A1), Twitter (A2), LinkedIn (A3), Google + (A4), and YouTube (A5). The initial decision making matrix

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1 The name is changed to protect the anonymity of the airline.

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### Table 2

<table>
<thead>
<tr>
<th>Criterion</th>
<th>Sub-Criterion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Content (C1)</td>
<td></td>
</tr>
<tr>
<td>Impression Score (C2)</td>
<td></td>
</tr>
<tr>
<td>Cost (C3)</td>
<td></td>
</tr>
<tr>
<td>Look and feel (C4)</td>
<td>User friendliness (C4.1)</td>
</tr>
<tr>
<td>Audience fit (C5)</td>
<td>Design (C5.1)</td>
</tr>
<tr>
<td></td>
<td>Educational level (C5.2)</td>
</tr>
<tr>
<td></td>
<td>Age (C5.3)</td>
</tr>
</tbody>
</table>

---

![Fig. 3. The network structure.](image-url)
which is a minimizing using Eq. (29). Following
above, using Eq. (26),
for the five so-
mined the relative significance of each alternative by calculating

\[ \text{Table 7} \]
Table 7 presents the “Look & Feel” \( (X_4) \) pairwise comparison matrix.

<table>
<thead>
<tr>
<th></th>
<th>( X_1 )</th>
<th>( X_2 )</th>
<th>( X_3 )</th>
<th>( X_4 )</th>
<th>( X_5 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
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<td>1.0000</td>
<td>1.0000</td>
<td>0.8209</td>
<td>1.5254</td>
</tr>
<tr>
<td>2</td>
<td>0.4228</td>
<td>0.6555</td>
<td>1.2181</td>
<td>1.0000</td>
<td>1.0000</td>
</tr>
<tr>
<td>3</td>
<td>0.1947</td>
<td>0.3376</td>
<td>0.6934</td>
<td>0.3998</td>
<td>0.7647</td>
</tr>
<tr>
<td>4</td>
<td>0.2441</td>
<td>0.3834</td>
<td>0.7647</td>
<td>0.2441</td>
<td>0.3834</td>
</tr>
<tr>
<td>5</td>
<td>0.2932</td>
<td>0.5302</td>
<td>1.0000</td>
<td>0.5078</td>
<td>0.8327</td>
</tr>
</tbody>
</table>

\[ \text{Table 4} \]
The “Design” \( (X_{42}) \) pairwise comparison matrix.

<table>
<thead>
<tr>
<th></th>
<th>( X_1 )</th>
<th>( X_2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.0000</td>
<td>1.0000</td>
</tr>
<tr>
<td>2</td>
<td>1.0000</td>
<td>1.0000</td>
</tr>
</tbody>
</table>

\[ \text{Table 5} \]
The initial super-matrix.

<table>
<thead>
<tr>
<th></th>
<th>( X_1 )</th>
<th>( X_2 )</th>
<th>( X_3 )</th>
<th>( X_4 )</th>
<th>( X_5 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
<td>0.8098</td>
</tr>
<tr>
<td>2</td>
<td>0.4801</td>
<td>0.9184</td>
<td>1.6398</td>
<td>1.0000</td>
<td>0.6934</td>
</tr>
</tbody>
</table>

\[ \text{Table 6} \]
The weighted super-matrix.

<table>
<thead>
<tr>
<th></th>
<th>( X_1 )</th>
<th>( X_2 )</th>
<th>( X_3 )</th>
<th>( X_4 )</th>
<th>( X_5 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.0000</td>
<td>0.3009</td>
<td>0.3643</td>
<td>0.3457</td>
<td>0.2785</td>
</tr>
<tr>
<td>2</td>
<td>0.1950</td>
<td>0.0000</td>
<td>0.1319</td>
<td>0.2834</td>
<td>0.2283</td>
</tr>
</tbody>
</table>

\[ \text{Table 8} \]
The relevant information for the seven cri-
tera and sub-criteria are presented in this table. All criteria are maxi-
izing criteria with the exception of \( \otimes X_5 \) which is a minimizing
criterion. The weights presented in this table are the importance
weights determined through the fuzzy ANP process. The values pre-
sented for the initial decision matrix are all interval values.

The initial decision matrix with interval values was then nor-
malized. The normalized decision matrix \( (\otimes X) \) is presented in Ta-
ble 9. The weighted decision matrix \( (\otimes X) \) presented in Table 10
was constructed next.

We then followed the procedure described earlier and deter-
mined the relative significance of each alternative by calculating \( \beta_1 \) using Eq. (26), \( K_i \) using Eq. (27), and \( Q_j \) using Eq. (29). Following
this step, we determined the utility degree of each alternative \( (N_j) \)
using Eq. (29). Table 11 presents the \( P_j, R_j, Q_j, \) and \( N_j \) for the five so-
cia media platforms under consideration.

As shown in Table 11, Facebook \( (A_1) \) with a utility degree of
100% was selected as the most suitable social media platform for
Trans-Gulf Airline. LinkedIn \( (A_2) \) with a utility degree of 99.1% was
selected as the second most suitable social media platform. You-
tube \( (A_3) \) with a utility degree of 94.0% was the third ranking
social media platform. Twitter \( (A_4) \) and Google+ \( (A_5) \) with utility
degrees of 82.8% and 80.4%, respectively, were selected as the fourth
and fifth choices for social media at Trans-Gulf. In summary, \( A_1 > A_3 > A_2 > A_4 \).
While platforms such as Facebook, Twitter, LinkedIn, Google+, and
YouTube have emerged as top social media sites for most companies,
these too often are treated as stand-alone marketing tools rather than as
an integrated part of the sales strategy (Hanna, Rohm, & Crittenden, 2011).
To this end, Trans-Gulf management decided to choose the top two platforms
of Facebook (to reach out networks of family and friends) and LinkedIn (to
reach out network of co-workers).

5. Conclusions and future research directions

The recent developments in computers and information tech-
nology have brought both opportunities and challenges in the glo-
bal and boundary-less world. Marketing managers are faced with a
dynamic and interconnected international environment and social
media sites have become important tools for businesses. Many
organizations now actively use social media platforms to promote
and market their products and services. Unlike conventional mar-
keting tools, social media applications allow users to have more
control of their choices by posting comments, sharing information,
or praising or criticizing products and services. Although traditio-
unal media are not disappearing, it is clear that major marketers
are shifting their budgets into new social media marketing opportu-
nities and applications. Traditional marketing, involving ex-
change of information in one direction, can no longer help
companies introduce all aspects of their products and show cus-
tomers that their needs are important. Social media facilitate
two-way communication and connect customers on a mass scale.

Despite these benefits, selecting the right social media platform
has been a difficult task because these problems are complex with
multiple and often conflicting criteria. Most existing social media
selection models are limited to simple classification charts catego-
rizing the different types of social media engagements or simple
decision trees highlighting the key decisions one must make when
choosing the right platform.

We proposed a novel analytical framework for social media
platform selection. The proposed hybrid framework integrates
the ANP with fuzzy set theory and the COPRAS-G method. The
ANP and fuzzy set theory were used to determine the importance
weight of the social media platform selection criteria. The COPRAS-
G method was used to rank and select the most suitable social
media platform. We presented a real-world case study and demon-
strated the applicability of the proposed framework.

The proposed framework is: (1) structured and systematic with
step-by-step and well-de fined procedures; (2) simple and
transparent with a straightforward computation process; (3) rational and logical with a sound mathematical and theoretical foundation; (4) supportive and informative with a scalar value that identifies both the best and worst social media platform simultaneously; (5) realistic and practical with the ability to deal with impreciseness and vagueness in real-world social media platform assessment problems; and (6) versatility and flexibility with the ability to be applied to other multi-criteria prioritization problems.

A stream of future research can extend our method by developing other hybrid approaches for the integrated use of our distance measure, not only for hybrids of different MADM methods but also for hybrids of multi-attribute value theory and numerical optimization.

### Table 8
The initial decision matrix.

<table>
<thead>
<tr>
<th>Criterion</th>
<th>Optimal</th>
<th>Weight</th>
<th>Initial decision matrix</th>
</tr>
</thead>
<tbody>
<tr>
<td>$X_1$</td>
<td>Max</td>
<td>0.2370</td>
<td>[70;80]</td>
</tr>
<tr>
<td>$X_2$</td>
<td>Max</td>
<td>0.1818</td>
<td>[90;55]</td>
</tr>
<tr>
<td>$X_3$</td>
<td>Min</td>
<td>0.1738</td>
<td>[80;90]</td>
</tr>
<tr>
<td>$X_4$</td>
<td>Max</td>
<td>0.1002</td>
<td>[60;70]</td>
</tr>
<tr>
<td>$X_5$</td>
<td>Max</td>
<td>0.1138</td>
<td>[70;80]</td>
</tr>
<tr>
<td>$X_6$</td>
<td>Max</td>
<td>0.1007</td>
<td>[65;75]</td>
</tr>
</tbody>
</table>

### Table 9
The normalized decision matrix.

<table>
<thead>
<tr>
<th>Criterion</th>
<th>Normalized decision matrix</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A_1$</td>
<td>$A_2$</td>
</tr>
<tr>
<td>$X_1$</td>
<td>[0.209:0.239]</td>
</tr>
<tr>
<td>$X_2$</td>
<td>[0.271:0.286]</td>
</tr>
<tr>
<td>$X_3$</td>
<td>[0.267:0.300]</td>
</tr>
<tr>
<td>$X_4$</td>
<td>[0.226:0.264]</td>
</tr>
<tr>
<td>$X_5$</td>
<td>[0.255:0.291]</td>
</tr>
<tr>
<td>$X_6$</td>
<td>[0.149:0.179]</td>
</tr>
<tr>
<td>$A_1$</td>
<td>[0.197:0.227]</td>
</tr>
</tbody>
</table>

### Table 10
The weighted decision matrix.

<table>
<thead>
<tr>
<th>Criterion</th>
<th>Weighted decision matrix</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A_1$</td>
<td>$A_2$</td>
</tr>
<tr>
<td>$X_1$</td>
<td>[0.050:0.057]</td>
</tr>
<tr>
<td>$X_2$</td>
<td>[0.049:0.052]</td>
</tr>
<tr>
<td>$X_3$</td>
<td>[0.046:0.052]</td>
</tr>
<tr>
<td>$X_4$</td>
<td>[0.023:0.026]</td>
</tr>
<tr>
<td>$X_5$</td>
<td>[0.029:0.033]</td>
</tr>
<tr>
<td>$X_6$</td>
<td>[0.014:0.017]</td>
</tr>
<tr>
<td>$A_1$</td>
<td>[0.020:0.023]</td>
</tr>
</tbody>
</table>

### Table 11
The evaluation of the utility degree.

<table>
<thead>
<tr>
<th></th>
<th>$p_1$</th>
<th>$p_2$</th>
<th>$Q_1$</th>
<th>$N_i$ (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A_1$</td>
<td>0.196</td>
<td>0.049</td>
<td>0.219</td>
<td>100.0</td>
</tr>
<tr>
<td>$A_2$</td>
<td>0.151</td>
<td>0.038</td>
<td>0.182</td>
<td>82.8</td>
</tr>
<tr>
<td>$A_3$</td>
<td>0.178</td>
<td>0.029</td>
<td>0.217</td>
<td>99.1</td>
</tr>
<tr>
<td>$A_4$</td>
<td>0.132</td>
<td>0.026</td>
<td>0.176</td>
<td>80.4</td>
</tr>
<tr>
<td>$A_5$</td>
<td>0.170</td>
<td>0.032</td>
<td>0.206</td>
<td>94.0</td>
</tr>
</tbody>
</table>

### References


