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Research Article

RANKING SOCIAL MEDIA PLATFORMS FOR EMPLOYMENT OPPORTUNITIES USING TOPSIS METHOD

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Abstract

In recent years, social media platforms have become essential tools for communication, marketing, and information sharing. This study applies the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), a multi-criteria decision-making method, to rank social media platforms based on criteria such as user engagement, popularity, content quality, and usability. The results demonstrate that TOPSIS provides a systematic and reliable framework for ranking alternatives and supports effective decision-making.
Keywords: TOPSIS, Social Media, MCDM, Ranking, Decision Making.

Introduction

This section presents the basic concepts and definitions required to understand the proposed methodology for ranking social media platforms using the TOPSIS method. The main components involved in this study include social networks, multi-criteria decision making (MCDM), and the TOPSIS technique.

Several studies have focused on identifying influential users in social networks using models based on real data and user interactions. Techniques such as influence propagation models, sentiment analysis, and ranking algorithms have been widely applied. Methods like Twitter Rank, an extension of PageRank, and SIR models have been used to analyse influence spread and user importance.

Researchers have also explored approaches based on trust networks, Leader Rank, and behavioural characteristics to improve influence analysis. However, many existing methods are computationally intensive and rely on limited criteria.

Recent studies highlight the effectiveness of multi-criteria decision-making methods such as TOPSIS for identifying influential nodes by considering multiple attributes simultaneously. Additionally, concepts like centrality measures, community detection, and homophily have contributed significantly to understanding social network structures.

Despite these advancements, there is still a need for efficient, multi-criteria approaches to accurately rank users in dynamic social networks.

1. Social Networks and Social Media

A social network refers to a digital platform that enables users to create profiles, connect with other users, and share information, opinions and multimedia content. Popular social networking platforms such as Facebook, Instagram, Twitter, YouTube and LinkedIn provide various services including communication, marketing, entertainment and professional networking. Each social media platform differs in terms of functionality, user base, content type and level of interaction. Therefore, selecting the most suitable social network depends on multiple performance criteria.

1.1 Multi-Criteria Decision Making (MCDM)

Multi-Criteria Decision Making (MCDM) is a decision-making approach used to evaluate and rank alternatives based on multiple, often conflicting, criteria. In real-world problems, a decision maker must consider several factors simultaneously, such as cost, quality, performance and risk. MCDM methods provide systematic procedures to analyze such complex problems and to identify the best alternative. In the context of social media selection, MCDM helps in evaluating different platforms based on criteria such as popularity, engagement, usability, security and marketing effectiveness.

1.2 Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

TOPSIS is a widely used MCDM method proposed by Hwang and Yoon. The basic principle of TOPSIS is that the best alternative should have the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution. The positive ideal solution represents the best possible performance for each criterion, while the negative ideal solution represents the worst performance.

The TOPSIS method involves constructing a decision matrix, normalizing the matrix, assigning weights to the criteria, determining the ideal and negative-ideal solutions, calculating the separation measures, and computing the relative closeness of each alternative to the ideal solution. Based on the closeness coefficient, the alternatives are ranked in descending order, and the alternative with the highest closeness value is considered the best choice.

2 Mathematical Concepts Used in TOPSIS

The TOPSIS method is based on several mathematical concepts which help in evaluating and ranking alternatives systematically. The important concepts used in this study are explained below.

2.1 Decision Matrix

A decision matrix is a table that represents alternatives and criteria. Each row represents an alternative and each column represents a criterion. The values in the matrix show the performance of each alternative with respect to each criterion.

It is represented as:

$X = [x_{ij}]$

where x_{ij} represents the performance value of the i^{th} alternative with respect to the j^{th} criterion.

2.2. Normalization

Normalization is used to convert different units of data into a comparable scale. This helps to eliminate the effect of different measurement units.

The normalized value is calculated using vector normalization:

$$r_{ij}=\frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$$

2.3. Weighted Normalized Matrix

Each criterion has a weight based on its importance. The normalized values are multiplied by their respective weights to obtain the weighted normalized matrix.

$V_{ij} = w_j \times r_{ij}$

where w_j is the weight of the j^{th} criterion.

2.4. Positive Ideal Solution (PIS)

Positive ideal solution represents the best possible value for each criterion.

$$A^+ = \{\max(V_{ij}) | j \epsilon J\}$$

2.5. Negative Ideal Solution (NIS)

Negative ideal solution represents the worst possible value for each criterion.

$$A^- = \{min(V_{ij}) | j \epsilon J\}$$

2.6. Separation Measures

This step calculates the distance of each alternative from the positive and negative ideal solutions using Euclidean distance.

$$S_i^+ = \sqrt{\sum_{j=1}^{n}(V_{ij} - A_j^+)2}\ , S_i^- = \sqrt{\sum_{j=1}^{n}(V_{ij} - A_j^-)2}$$

2.7. Closeness Coefficient

The relative closeness of each alternative to the ideal solution is calculated as:

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-}$$

The alternative with the highest closeness coefficient is ranked first.

3 Ranking the Using TOPSIS Method

3.1 METHODOLOGY

This study employs the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method to identify influential users in a social network. TOPSIS is a well-known Multi-Criteria Decision-Making (MCDM) technique that ranks alternatives based on their distance from an ideal best and an ideal worst solution. In social network analysis, each user is considered an alternative, and network centrality measures are treated as decision criteria.

Step 1: Selection of Alternatives and Criteria

In the first step, the set of social media platforms to be evaluated is identified. These platforms represent the alternatives in the decision-making problem. Typical alternatives considered in this study include Facebook, Instagram, Twitter, YouTube and LinkedIn.

Next, a set of evaluation criteria is selected based on the objectives of the study and a review of related literature. Common criteria used for ranking social media platforms include user engagement, popularity, ease of use, content quality, accessibility, security and marketing effectiveness. Each criterion reflects an important aspect of social media performance.

Step 2: Construction of the Decision Matrix

A decision matrix is constructed in which each row represents a social media platform (alternative) and each column represents an evaluation criterion. The elements of the matrix indicate the performance score of each platform with respect to each criterion. These values may be obtained from surveys, expert opinions, questionnaires or secondary data sources. The decision matrix can be represented as:

where x_{ij} denotes the performance of the i^{th} alternative with respect to the criterion, j^{th} is the number of alternatives and n is the number of criteria.

Step 3: Normalization of the Decision Matrix

Since the criteria may be measured in different units, the decision matrix is normalized to transform all values into a comparable scale. Vector normalization is commonly used and is given by:

$$r_{ij}=\frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$$

where r_{ij} represents the normalized value of x_{ij}.

Step 4: Construction of the Weighted Normalized Matrix

In this step, weights are assigned to each criterion according to their relative importance. The weights may be determined using expert judgment, survey results or weighting methods such as entropy or AHP. The normalized values are multiplied by the corresponding criterion weights to obtain the weighted normalized matrix:

$$V_{ij} = w_j \times r_{ij}$$

where w_j denotes the weight of the j^{th} criterion and $\sum_{j=1}^{n} w_j = 1$

Step 5: Determination of Positive Ideal and Negative Ideal Solutions

The positive ideal solution (PIS) and negative ideal solution (NIS) are determined from the weighted normalized matrix. The PIS consists of the best values of each criterion, while the NIS consists of the worst values. They are defined as:

$$A^+ = \{\max(V_{ij}) | j \epsilon J\}, \quad A^- = \{min(V_{ij}) | j \epsilon J\}$$

where J denotes the set of benefit criteria and cost criteria accordingly.

Step 6: Calculation of Separation Measures

The Euclidean distance of each alternative from the positive ideal solution and the negative ideal solution is calculated as:

$$S_i^+ = \sqrt{\sum_{j=1}^{n}(V_{ij} - A_j^+)2}, S_i^- = \sqrt{\sum_{j=1}^{n}(V_{ij} - A_j^-)2}$$

where S_i^+ and S_i^- denote the distances from the positive and negative ideal solutions respectively.

Step 7: Computation of Closeness Coefficient and Ranking

The relative closeness of each alternative to the ideal solution is computed using: $$C_i = \frac{S_i^-}{S_i^+ + S_i^-}$$

The alternatives are then ranked in descending order based on the closeness coefficient C_i The platform with the highest closeness value is considered the most suitable social media platform.

Step 8: Final Ranking and Decision Making

Finally, the ranking results are analyzed and the best social media platform is identified. The obtained ranking helps decision makers select the most appropriate social network based on multiple criterion

Flow chart

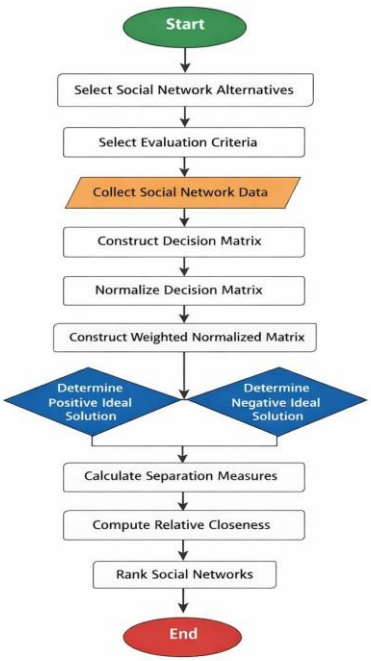


Figure 1. Flow Chart

4 NUMERICAL ANALYSIS

In the study the selection of alternative and criteria is based on the social media usage pattern and employment related requirements of users in Cuddalore district

The alternativeis chosen as popular social media platforms that are commonly used by students,job seekers, and working professionals in the Cuddalore district. Platforms such as LinkedIn, Twitter(X), Facebook, Instagram and YouTube are selected because they are relevant to the employment needs of people in the Cuddalore district. Criteria such as job opportunities, professional networking, recruiter visibility, skill promotion, and time consumption reflect the key aspects considered by local users while choosing a social media platform for career growth. Thus, alternatives represent the social media platforms used in the Cuddalore district, and criteria represent the employment-oriented factors influencing their selection. These criteria are combined using the TOPSIS method to identify the most suitable platform for job-related purposes in the district.

TOPSIS Steps:

Alternative (social media platforms)
Let the alternative be
A1 = LinkedIn
A2 = Twitter (x)
A3 = Facebook
A4 = Instagram
A5 = YouTube
Criteria (Evaluation Factors)

We choose job related criteria

Symbol	Criteria	Type
C1	Job Opportunities	Benefit
C2	Professional Networking	Benefit
C3	Recruiter Visibility	Benefit
C4	Skill Promotion	Benefit
C5	Time consumption	Benefit

Decision Matrix (x)

Alternatives	C1	C2	C3	C4	C5
LinkedIn	9	9	9	8	6
Twitter	6	7	6	7	7
Facebook	6	6	6	6	7
Instagram	5	6	5	8	8
YouTube	7	5	7	9	6

Weights of Criteria

Criteria	C1	C2	C3	C4	C5
Weights	0.25	0.20	0.20	0.20	0.15

Step :1 Normalization formula

rij= $\frac{xij}{\sqrt{\sum xij^2}}$

C1:

$\sqrt{9^2+6^2+5^2+6^2+7^2} = \sqrt{81+36+25+36+49} = \sqrt{227}$

$= 15.07$

C2:

$\sqrt{9^2+7^2+6^2+6^2+5^2} = \sqrt{81+49+36+36+25} = \sqrt{227}$

$= 15.07$

C3:

$\sqrt{9^2+6^2+5^2+6^2+7^2} = \sqrt{81+36+25+36+49} = \sqrt{227}$

$= 15.07$q

C4:

$\sqrt{8^2+7^2+8^2+6^2+9^2} = \sqrt{64+49+64+36+49} = \sqrt{294}$

$= 17.15$

C5:

$\sqrt{6^2+7^2+8^2+7^2+6^2} = \sqrt{36+49+64+49+36} = \sqrt{234}$

Normalized Decision matrix

Alternative	C1	C2	C3	C4	C5
LinkedIn	0.597	0.597	0.597	0.467	0.391
Twitter	0.398	0.464	0.398	0.408	0.457
Facebook	0.398	0.398	0.398	0.350	0.457
Instagram	0.332	0.398	0.332	0.467	0.522
YouTube	0.464	0.332	0.464	0.525	0.391

Step 2 : $V_{ij} = w_j \times r_{ij}$

Alternatives	C1	C2	C3	C4	C5
LinkedIn	0.149	0.119	0.119	0.093	0.059
Twitter	0.100	0.093	0.080	0.082	0.069
Facebook	0.100	0.080	0.080	0.070	0.069
Instagram	0.083	0.080	0.066	0.093	0.078
YouTube	0.116	0.066	0.093	0.105	0.059

Step 3: Ideal Best (A^+)& Ideal Worst (A^-)

Criteria	A^+	A^-
C1	0.149	0.083
C2	0.119	0.066
C3	0.119	0.066
C4	0.105	0.070
C5	0.059	0.078

Step 4: Separation Measures

$$S_i^+ = \sqrt{\sum (V_{ij} - Aj^+)^2}$$

LinkedIn

$$\sqrt{(0.149-0.149)^2+(0.119-0.119)^2+(0.119-0.119)^2+(0.093-0.105)^2+(0.059-0.059)^2} = 0.012$$

Twitter

$$\sqrt{(0.100-0.149)^2+(0.093-0.119)^2+(0.080-0.119)^2+(0.082-0.105)^2+(0.069-0.059)^2} = 0.075$$

Facebook

$$\sqrt{(0.100-0.149)^2+(0.080-0.119)^2+(0.080-0.119)^2+(0.070-0.105)^2+(0.069-0.059)^2} = 0.071$$

Instagram

$$\sqrt{(0.083-0.149)^2+(0.080-0.119)^2+(0.066-0.119)^2+(0.093-0.105)^2+(0.078-0.059)^2} = 0.088$$

YouTube

$$\sqrt{(0.116-0.149)^2+(0.066-0.119)^2+(0.093-0.119)^2+(0.105-0.105)^2+(0.059-0.059)^2} = 0.041$$

Distance from negative ideal

$$S_i^+ = \sqrt{\sum (V_{ij} - A_j^+)^2}$$

LinkedIn

$$\sqrt{(0.149-0.083)^2+(0.119-0.066)^2+(0.119-0.066)^2+(0.093-0.070)^2+(0.059-0.078)^2} = 0.094$$

Twitter

$$\sqrt{(0.100-0.083)^2+(0.093-0.066)^2+(0.080-0.066)^2+(0.082-0.070)^2+(0.069-0.078)^2} = 0.039$$

Facebook

$$\sqrt{(0.100-0.083)^2+(0.080-0.066)^2+(0.080-0.066)^2+(0.070-0.070)^2+(0.069-0.078)^2} = 0.038$$

Instagram

$$\sqrt{(0.083-0.083)^2+(0.080-0.066)^2+(0.066-0.066)^2+(0.093-0.070)^2+(0.078-0.078)^2} = 0.023$$

Youtube

$$\sqrt{(0.116-0.083)^2+(0.066-0.066)^2+(0.093-0.066)^2+(0.105-0.070)^2+(0.059-0.078)^2} = 0.067$$

Alternatives	S^+	S^-
linkedIn	0.012	0.094
Twitter	0.075	0.039
facebook	0.071	0.038
Instagram	0.088	0.067

Step 5: Closeness Coefficient

$$CCi = \frac{S_i^-}{S_i^+ + S_i^-}$$

$$\text{LinkedIn} = \frac{0.094}{0.012+0.094} = \frac{0.094}{0.106} = 0.887$$

$$\text{Twitter} = \frac{0.039}{0.075+0.039} = \frac{0.039}{0.114} = 0.342$$

$$\text{Facebook} = \frac{0.038}{0.071+0.038} = \frac{0.038}{0.109} = 0.348$$

$$\text{Instagram} = \frac{0.023}{0.088+0.023} = \frac{0.023}{0.111} = 0.207$$

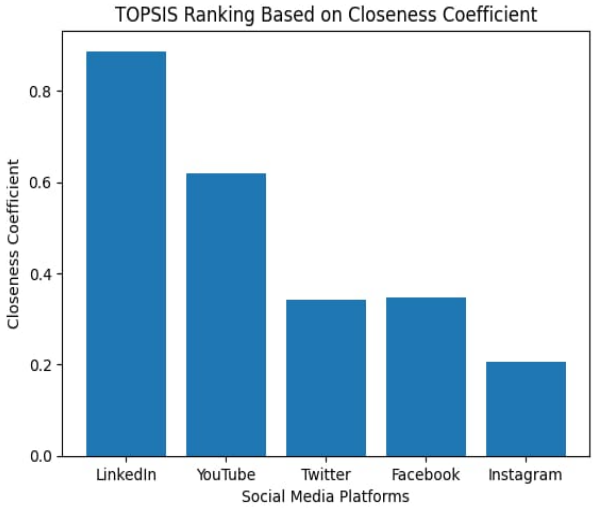
$$\text{YouTube} = \frac{0.067}{0.041+0.067} = \frac{0.067}{0.108} = 0.620$$

Final Ranking

Alternatives	Closeness Coefficient	Rank
LinkedIn	0.887	1
YouTube	0.620	2
Twitter	0.342	3
Facebook	0.348	4
Instagram	0.207	5

LinkedIn – The best Platform for Job search.

Bar chart



CONCLUSION

This study demonstrates that the TOPSIS method is an effective tool for ranking social media platforms based on multiple criteria such as engagement, popularity, and usability. The results provide a clear and objective ranking, helping decision-makers select the most suitable platform. Overall, TOPSIS offers a reliable, systematic, and flexible approach for multi-criteria decision-making and can be extended to various real-world applications.

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