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AN IMPROVED COCOSO FRAMEWORK UNDER HESITANCY AND INCONSISTENCY: APPLICATION IN INFLUENCER SELECTION

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Abstract. Influencer marketing has become a core component of digital advertising, yet selecting the most suitable influencer remains a complex multi-criteria problem. Despite its growing importance, research on systematic influencer selection frameworks—particularly those addressing hesitancy and inconsistency in expert judgment—remains limited. This study proposes a decision-making framework integrating Dempster–Shafer theory with Multi-Criteria Decision-Making (MCDM) techniques to address hesitant evaluations. Moreover, Murphy's combination rule replaces the traditional Dempster–Shafer rule to manage inconsistent assessments more effectively. Objective criteria weights are derived using the CRiteria Importance Through Intercriteria Correlation (CRITIC) and the Method based on the Removal Effects of Criteria (MEREC) methods, reducing subjectivity while accounting for information variability, inter-criteria correlation, and removal effects. The Borda rule is applied to aggregate the utility functions of the Combined Compromise Solution (CoCoSo) method, ensuring fairer ranking results. A case study conducted in a beauty technology company, based on data from experienced professionals, validates the proposed model. The results confirm that the Dempster–Shafer–based CRITIC–MEREC–CoCoSo framework provides a reliable, interpretable and data-driven tool for effective influencer selection.

Keywords: influencer marketing, MCDM, Dempster–Shafer theory, CRITIC, MEREC, CoCoSo.

JEL Classification: C44, M31.

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1. Introduction

In the era of digital transformation, influencer marketing has emerged as a cornerstone of modern advertising strategy, reshaping the way brands communicate with consumers. As traditional media continues to lose traction among younger, digitally native audiences, social media influencers have become powerful intermediaries, capable of shaping opinions, driving consumer engagement, and enhancing brand equity (Migkos et al., 2025). The global influencer marketing industry is projected to reach USD 32.5 billion by 2025, highlighting its growing commercial and strategic importance (Ross, 2025). Despite its rapid growth, selecting suitable influencers remains a critical challenge for marketing managers. The proliferation of influencers across platforms such as Instagram, YouTube, TikTok, and X has created a complex decision environment involving large choice sets, heterogeneous performance indicators, and unstable audience engagement. Appropriate influencer selection can improve brand awareness, authenticity, and consumer trust, whereas inappropriate choices may reduce campaign effectiveness and create reputational risks (Bala et al., 2024; Qian & Park, 2021). Thus, the selection of suitable influencers remains a critical decision for organizations (Leung et al., 2022).

Existing studies have applied optimization models (Mallipeddi et al., 2022; Ye et al., 2024; Zhang et al., 2024), machine learning (Ramya & Bagavathi, 2025; Ye et al., 2024), and Multi-Criteria Decision-Making (MCDM) frameworks (Gandhi & Muruganantham, 2015; Lim et al., 2021). However, optimization models and machine learning approaches often struggle to effectively incorporate qualitative knowledge provided by industry experts. For instance, assessing intangible attributes such as influencer expertise and trustworthiness relies heavily on subjective human judgment. Moreover, due to their reliance on complex algorithmic structures, these techniques frequently lack transparency and provide limited interpretability for decision-makers (DMs). In contrast, MCDM provides a structured and interpretable framework for simultaneously evaluating multiple criteria while integrating quantitative information and qualitative judgments (Garcia-Garcia, 2022). It is therefore well suited to influencer selection under uncertainty.

As influencer marketing grows more complex, DMs must balance diverse evaluation criteria amidst uncertainty and incomplete information (Leung et al., 2022). This difficulty stems from the nature of the data itself. For example, metrics such as follower counts may fail to capture the true impact of influencers because they can be artificially inflated. Such uncertainty may result in hesitation and inconsistent evaluations among DMs. Nevertheless, current MCDM models have limitations in handling influencer selection under uncertainty. Advanced extensions of fuzzy set theory, such as type-2 fuzzy sets (Mendel, 2017), and intuitionistic fuzzy sets (Li, 2005), still fail to capture DMs' hesitation across multiple evaluation levels. Although hesitant fuzzy sets (Torra, 2010) can handle this problem, they still struggle to capture inconsistencies in individual judgments under uncertainty. Moreover, traditional aggregation methods that rely on simple averaging may obscure differences in DM's opinions, thereby reducing the robustness of the group consensus (Zhao et al., 2024). While Dempster-Shafer theory provides a mechanism for DMs to express hesitation and aggregate inconsistent evaluations (Fei et al., 2019), its combination rule fails to handle completely conlficting assessments and produces counterintuitive results (Yong et al., 2004).

Moreover, criteria weights significantly influence influencer selection decisions, yet determining appropriate weights remains challenging due to limited information and knowledge. While subjective weighting approaches such as the Analytic Hierarchy Process (AHP), Best-Worst Method (BWM), and Full Consistency Method (FUCOM) depend on subjective judgments, objective weighting approaches derive weights from the characteristics of data, offering greater consistency and reliability. Among these, the CRITIC (CRiteria Importance Through Intercriteria Correlation) and MEREC (Method based on Removal Effects of Criteria) techniques have received considerable attention for their complementary strengths. The CRITIC method captures both the amount of information and the interrelationships among criteria, while MEREC assesses the impact of removing each criterion on the overall decision outcome (Lendvai et al., 2025; Wan et al., 2023). A combined CRITIC–MEREC weighting scheme thus provides a more comprehensive mechanism for determining criteria importance in uncertain environments. In addition, Combined Compromise Solution (CoCoSo) method, proposed by Yazdani et al. (2018), is a novel ranking method based on three utility functions. This technique determines the final ranking solely from the values obtained through these functions, without considering the relative ranking within each utility function. Consequently, its ability to clearly explain the rationale behind the final ranking is limited (Lin et al., 2020). Therefore, it is important to take into account both the ranking values and their corresponding positions when producing the final results.

Given these challenges and opportunities, this study aims to develop a decision-making support model for influencer selection that:

- Integrates Dempster–Shafer theory into the MCDM framework to address DMs' hesitation across multiple evaluation levels, as it allows DMs to express their opinions through multiple basic probability assignments. Moreover, Dempster-Shafer theory also offers a combination rule to handle inconsistencies in DMs' evaluations.
- Adopts Murphy's combination rule (Murphy, 2000) to replace the original Dempster-Shafer rule to ensure reasonable results.
- Employs a hybrid CRITIC–MEREC method to provide more comprehensive objective criteria weights, as multiple characteristics of the criteria are considered simultaneously.
- Modifies the CoCoSo method by incorporating the Borda rule to produce fairer ranking results, as it considers both raw scores and rankings in the final evaluation.

Accordingly, this study aims to make several critical contributions to both theory and practice.

- First, this study contributes to decision-making research by developing a unified framework that simultaneously addresses hesitancy and inconsistency in group decision-making under uncertainty. Unlike conventional MCDM approaches, which typically treat these challenges separately, the proposed framework integrates them within a single evidence-based decision-making process. This extends the application of evidence theory to complex group decision environments.
- Second, the study expands the influencer marketing literature by conceptualizing influencer selection as a structured multi-criteria decision-making problem rather than relying primarily on individual performance indicators, such as follower count or engagement rate.
- Third, the proposed Dempster–Shafer–CRITIC–MEREC–Borda–CoCoSo framework enriches the MCDM literature by integrating evidence aggregation, objective criteria weighting, and compromise ranking within a unified decision-support model. It simultaneously addresses uncertainty, conflicting expert judgments, objective weight determination, and ranking stability.
- Finally, the practical value of the proposed framework is demonstrated through an influencer selection case study and comprehensive robustness analyses, including comparative analysis, sensitivity analysis, and rank-reversal testing.

The remainder of this paper is structured as follows. Section 2 reviews relevant literature on influencer marketing and existing influencer selection approaches. Section 3 presents the proposed MCDM framework, including Dempster-Shafer theory, Murphy's combination rule, CRITIC–MEREC weighting and Borda-CoCoSo ranking procedures. Section 4 provides a case study to demonstrate the applicability and validity of the proposed method. Section 5 discusses theoretical and managerial implications, and Section 6 concludes with key findings, limitations, and directions for future research.

2. Literature review

This section highlights the importance of influencer marketing and reviews related works.

2.1. Influencer marketing

Influencer marketing has emerged as one of the fastest-growing segments within the marketing and advertising industry. From a market size of $1.7 billion in 2015, the sector has experienced substantial growth, reaching an estimated $24 billion in 2024, with projections indicating a further expansion to over $32.5 billion by 2025 (Ross, 2025). Due to its significant impact on the global economy, influencer marketing has been extensively adopted across numerous platforms and countries (Vrontis et al., 2021). Many studies have focused on the attributes of influencers and their relationship with trust in advertising. For example, Lou and Yuan (2019) demonstrated that influencers' expertise and trustworthiness play important roles in enhancing brand awareness and purchase intention. Other studies have examined aspects of social media influence in marketing, such as opinion leadership and parasocial relationships (Fakhreddin & Foroudi, 2022; Reinikainen et al., 2020). Furthermore, Farivar et al. (2021) pointed out that both opinion leadership and parasocial relationships significantly influence purchase intention, although parasocial relationships tend to exert a stronger impact on consumers' purchasing decisions. Several studies have compared social media influencers with traditional celebrities; however, the findings on which type of endorser is more effective remain inconclusive (Fan et al., 2023; Jin et al., 2019). Importantly, the literature consistently emphasizes the importance of selecting the right influencer, as it directly affects marketing outcomes (Aw & Agnihotri, 2024; Leung et al., 2022; Vrontis et al., 2021). Therefore, developing systematic frameworks to support influencer selection remains a critical research direction in the influencer marketing field.

2.2. Handling hesitancy and inconsistency in MCDM methods

MCDM methods are explicitly designed to address decision problems characterized by heterogeneous, and sometimes conflicting criteria (Garcia-Garcia, 2022). These methods provide transparent and interpretable decision support while allowing DMs to incorporate managerial judgment into the evaluation process (Qu et al., 2017). Consequently, MCDM approaches are particularly suitable for influencer selection, where decisions often involve subjective evaluations.

Despite the critical role of selecting appropriate influencers in driving marketing success, research on MCDM frameworks for influencer selection remains limited. One of the few attempts to develop such a model was presented by Gandhi and Muruganantham (2015). In the study, the authors applied the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method to identify potential influencers across social media platforms. Another model was developed by Lim et al. (2021) to support the selection of livestreamers. These studies adopted Type-1 fuzzy sets (Zimmermann, 2010) to address the inherent vagueness in DMs' subjective evaluations, in which membership values are represented by crisp numbers between 0 and 1. A significant drawback of Type-1 fuzzy sets is the crisp nature of their membership functions, which may not adequately capture subjective variations found in real-world decision-making environments. To overcome this limitation, the literature has proposed several advanced fuzzy set extensions. For example, Type-2 fuzzy sets extend traditional fuzzy sets by allowing membership values themselves to be fuzzy sets (Mendel, 2017). Interval-valued fuzzy sets represent membership degrees as intervals (Cornelis et al., 2006). Intuitionistic fuzzy sets incorporate both membership and non-membership degrees (Li, 2005). Nevertheless, these approaches still struggle to capture DMs' hesitation arising from limited information about influencer performance. To address this issue, hesitant fuzzy sets were proposed to allow DMs to express their hesitation among multiple possible evaluation values simultaneously (Torra, 2010).

Another challenge in influencer selection is inconsistent assessments among DMs, as differences in expertise and perspectives may lead to divergent evaluations. Although such divergence may complicate decision-making and hinder consensus, it can also provide valuable insights by reflecting different perspectives. However, many existing MCDM approaches rely on simple averaging methods to aggregate evaluations, which may lead to information loss and overlook the diversity of expert opinions (Zhao et al., 2024). To address this drawback, more advanced aggregation techniques are required to preserve and utilize the diversity of DMs' inputs. Dempster–Shafer theory, also known as evidence theory, provides a mathematical framework for combining information from multiple sources under uncertainty (Deng & Chan, 2011). This theory allows DMs to express hesitant evaluations and effectively handles heterogeneity among DMs' opinions through its combination rule (Fei et al., 2019). Therefore, Dempster–Shafer theory represents a suitable approach for addressing hesitation and inconsistency in complex decision-making problems involving subjective judgments, such as influencer selection.

2.3. Exploring weighting methods

Criteria weighting plays a pivotal role in the decision-making process, as the relative importance of criteria directly influences the final outcome. Broadly, weighting methods can be classified into two categories: subjective and objective. Subjective methods, including AHP (Nadeem et al., 2025), SWARA (Sithi et al., 2025), FUCOM (Yürüyen et al., 2025), and BWM (Li & Fei, 2025), rely on judgments to assign importance to criteria. However, they are vulnerable to biased evaluations, particularly in highly uncertain environments. To mitigate such biases, objective weighting methods are often preferred, as they derive weights directly from the intrinsic properties of the data. Prior research has proposed a variety of objective approaches, including the entropy method (Chen, 2021), variance method (Li et al., 2019), CRITIC method (Liu et al., 2025) and MEREC method (Komasi et al., 2025). A comparison of these approaches is summarized in Table 1.

Table 1. Comparison of objective weighting methods

Methods	Consider data variability	Consider correlation	Consider removal effect
Entropy method	Yes	No	No
Variance method	Yes	No	No
CRITIC method	Yes	Yes	No
MEREC method	No	No	Yes

As shown in Table 1, the CRITIC method accounts for both information content and correlations among criteria, while the MEREC method considers the removal effect of each criterion. Therefore, combining these two approaches yields a more comprehensive weighting scheme.

3. Proposed model

This section begins with a summary of the proposed model, followed by a detailed stepwise process.

3.1. Overview of the proposed model

The proposed model is summarized as shown in Figure 1, which outlines three main stages:

Stage 1: Collect and aggregate data

After identifying potential influencers and defining the selection criteria, DMs evaluate influencers based on various performance metrics. Under Dempster-Shafer theory, DMs can assign their belief to multiple significance levels. The assessments are consolidated using the Murphy's combination rule (Murphy, 2000) and the pignistic function (Smets & Kennes, 1994).

Stage 2: Derive criteria weights

Based on decision matrix *S*, the CRITIC-MEREC method is applied to determine criteria weights. First CRITIC weights are computed to consider data variability and correlation coefficients. Second, MEREC method is applied to obtain weights based on removal effects. Third, the final weights are calculated by combing results from the two methods.

Stage 3: Compute the performance of influencers and rankings

Finally, using the decision matrix ***S*** obtained in Stage 1 and the criteria weights derived in Stage 2, the performance scores of influencers are calculated using the improved CoCoSo method.

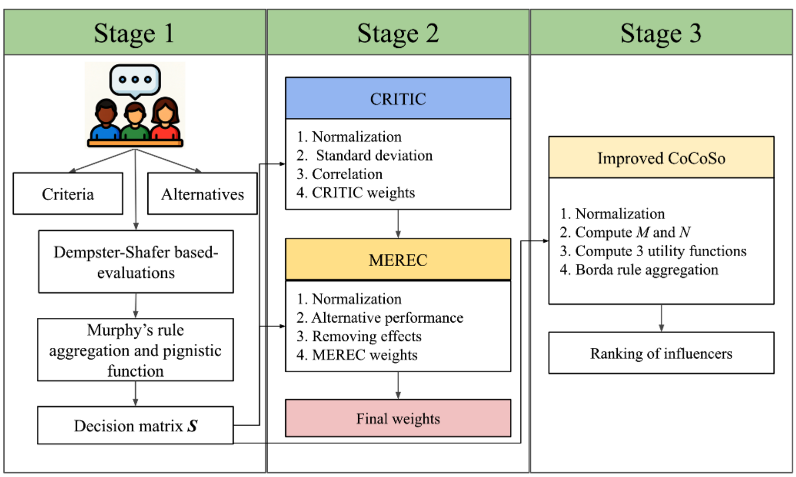

Figure 1. Flowchart

3.2. Stepwise analysis process

Stage 1: In this stage, Dempster-Shafer theory is applied to collect DMs' assessments.

The set of significance levels is denoted by $\theta = \{VL, L, M, H, VH\}$ and 2^{θ} represents the power set, which includes 32 (2^5) possible combinations of these levels (Deng & Chan, 2011). Their linguistic scale and corresponding significance levels are presented in Table 2.

Table 2. Evaluation levels

Significance levels	Code	Corresponding values
Very Low	VL	1
Low	L	2
Medium	M	3
High	H	4
Very High	VH	5

Assume there are h DMs, m potential influencers and n selection criteria, denoted by $D = \{D_1, D_2, ..., D_h\}$; $A = \{A_1, A_2, ..., A_m\}$ and $C = \{C_1, C_2, ..., C_n\}$, respectively. The k-th DM's evaluation for the i-th influencer with respect to the j-th criteria is represented as $D_{ij}^k = \{d_{1ij}^k, d_{2ij}^k, \ldots, d_{32ij}^k\}$, where $k = 1,2,\ldots,h$; $i = 1,2,\ldots,m$; $j = 1,2,\ldots,n$; and each of these elements denotes the degree of belief assigned by the DM to a subset of θ. These values must be non-negative and satisfy $d_{1ij}^k + d_{2ij}^k + \ldots + d_{32ij}^k = 1$.

The k-th DM's assessments can then be expressed in the basic probability assignment (BPA) form as in Eq. (1):

$$m_{ij}^k = \{\left(R, m_{ij}^k\left(R\right)\right) : R \subseteq \theta, m_{ij}^k\left(R\right) > 0\}, \tag{1}$$

where R denotes a subset in the power set and $m_{ij}^k\left(R\right) \in D_{ij}^k$.

Traditionally, the Dempster–Shafer combination rule has been employed to aggregate the evidence provided by DMs. However, this rule may yield counterintuitive outcomes and becomes unreliable when the assessments of DMs are in complete conflict (Zadeh, 1979). To address these limitations, the literature proposes several alternative combination rules such as Yager's rule (Yager, 1987) and Deng's rule (Yong et al., 2004). While Yager's rule has been questioned for its reasonableness by Yang and Xu (2013), Deng's rule involves a high level of computational complexity. This study adopts Murphy's combination rule (Murphy, 2000). The technique shows advantages over other combination rules by requiring low computation time and consistently producing reasonable results (Chen & Deng, 2023; Zhang & Deng, 2019). The method first computes the average of the BPAs from all DMs across the predefined significance levels, as expressed in Eq. (2):

$$\overline{m_{ij}}\left(R\right) = \frac{1}{h}\sum\nolimits_{1}^{h} m_{ij}^k\left(R\right). \tag{2}$$

The resulting average BPA is then combined with itself, as represented in Eq. (3):

$$m_{ij}^{Mu}\left(R\right) = \frac{1}{1-k_{ij}}\sum\nolimits_{B\cap C=R}\overline{m_{ij}}\left(B\right)\overline{m_{ij}}\left(C\right), \tag{3}$$

where $B, C \in 2^{\theta}$ and v_{ij} denotes the conflict level between two BPAs under alternative A_i and criteria C_j as computed by Eq. (4):

$$v_{ij} = \sum\nolimits_{B\cap C=\varnothing}\overline{m_{ij}}\left(B\right)\overline{m_{ij}}\left(C\right). \tag{4}$$

The process is conducted $h - 1$ times, where h denotes the number of DMs and the values of $m_{ij}^{Mu}\left(R\right)$ are updated after each iteration.

Due to the uncertainty in BPAs, the pignistic function converts BPAs into probabilities to facilitate decision-making (Smets & Kennes, 1994), as shown in Eq. (5):

$$\mathrm{BetP}(x)_{ij} = \sum_{x\in R, R\subseteq\Theta} \frac{1}{|R|}\frac{m_{ij}^{Mu}(R)}{1-m(\varnothing)}, \tag{5}$$

where $\mathrm{BetP}(x)_{ij}$ denotes pignistic probability of the significance level x under criteria j and alternative i, $|R|$ represents the number of elements in set R and $m(\varnothing)$ denotes the empty set.

Suppose significance levels, VL, L, M, H and VH, have associated scoring values r_1, r_2, r_3, r_4 and r_5 respectively. The crisp score of the evaluation for the i-th alternative with respect to the j-th criteria is then computed as in Eq. (6):

$$s_{ij} = BetP(VL)_{ij}\times r_1 + BetP(L)_{ij}\times r_2 + BetP(M)_{ij}\times r_3 + BetP(H)_{ij}\times r_4 + BetP(VH)_{ij}\times r_5. \tag{6}$$

Finally, the decision matrix is constructed as $\boldsymbol{S} = \left[s_{ij}\right]_{m\times n}$.

Stage 2: Based on the decision matrix, the criteria's importance is obtained objectively based on the CRTIC-MEREC method. The CRITIC–MEREC method was adopted because it combines two complementary objective weighting mechanisms. CRITIC determines criteria importance based on data variability and inter-criteria conflict, whereas MEREC evaluates the influence of each criterion through its removal effect on the overall evaluation.

The CRITIC method is proposed by Diakoulaki et al. (1995) to objectively determine criteria weights based on standard deviation and correlation relationship. The computation process is as follows. The normalized value s_{ij}^C for benefit criteria and cost criteria is determined by Eqs. (7) and (8), respectively. Benefit criteria are those for which higher values indicate better performance, whereas for cost criteria, higher values indicate lower performance.

$$s_{ij}^C = \frac{s_{ij} - s_j^-}{s_j^{\pm} s_j^-}, \quad i = 1,2\ldots,m,\ j = 1,2\ldots,n; \tag{7}$$

$$s_{ij}^C = \frac{s_{ij} - s_j^+}{s_j^+ - s_j^-}, \quad i = 1,2\ldots,m,\ j = 1,2\ldots,n, \tag{8}$$

where s_{ij}^C is the normalized value of the decision matrix of i-th criteria in the j-th criteria and $s_j^+ = \max\left(s_{1j}, s_{2j}, \ldots, s_{mj}\right)$ and $s_j^- = \min\left(s_{1j}, s_{2j}, \ldots, s_{mj}\right)$.

The correlation coefficient ρ_{jf} between the j-th and f-th criteria is obtained using Eq. (9):

$$\rho_{jf} = \sum_{i=1}^{m}\left(s^C{}_{ij} - \overline{s_j^C}\right)\left(s^C{}_{if} - \overline{s_f^C}\right) \Big/ \sqrt{\left(\sum_{i=1}^{m}\left(s^c{}_{ij} - \overline{s^C{}_j}\right)^2\right)\left(\sum_{i=1}^{m}\left(s^C{}_{if} - \overline{s_f^C}\right)^2\right)}, \tag{9}$$

where $\overline{s^C{}_j} = \sum_{i=1}^{m} s_{ij}^C$ and $\overline{s^C{}_f} = \sum_{i=1}^{m} s_{if}^C$.

Equation (10) is used to determine the standard deviation σ_j of each criterion, thereby capturing the dispersion in the assessment data.

$$\sigma_j = \sqrt{\frac{1}{n-1}\sum_{j=1}^{n}\left(s^C{}_{ij} - \overline{s_j^C}\right)^2}, \quad i = 1,2\ldots,m. \tag{10}$$

The index Q_j is calculated using Eq. (11):

$$Q_j = \sigma_j \sum_{j=1}^{n} \left(1 - \rho_{jf}\right). \tag{11}$$

The CRITIC weights of the criteria are determined using Eq. (12):

$$w_j^C = \frac{Q_j}{\sum_{j=1}^{n} Q_j}. \tag{12}$$

MEREC is a novel objective weighting method based on the removal effects of criteria (Keshavarz-Ghorabaee et al., 2021). The normalized values s_{ij}^M in the MEREC method are obtained using Eqs. (13) and (14) for benefit criteria and cost criteria respectively.

$$s_{ij}^M = \frac{\min_i s_{ij}}{s_{ij}}; \tag{13}$$

$$s_{ij}^M = \frac{s_{ij}}{\max_i s_{ij}}. \tag{14}$$

The performance of each alternative is computed as shown in Eq. (15):

$$Y_i = \ln\left(1 + \left(\frac{1}{m} \sum_j \left|\ln\left(s_{ij}^M\right)\right|\right)\right) \tag{15}$$

where Y_i is the performance of alternative A_i.

The overall performance of the i-th alternative when the f-th criterion is removed is computed as shown in Eq. (16):

$$Y_{ij}' = \ln\left(1 + \left(\frac{1}{m} \sum_{j, j \neq f}^{n-1} \left|\ln\left(s_{ij}^M\right)\right|\right)\right). \tag{16}$$

The removing effect of criterion C_j is calculated using Eq. (17):

$$E_j = \sum_i^m \left|Y_{ij}' - Y_i\right|. \tag{17}$$

The weights of the criteria under the MEREC method are derived as in Eq. (18):

$$w_j^M = \frac{E_j}{\sum_j^n E_j}. \tag{18}$$

Equation (19) is used to obtain the combined criteria, ensuring that the final weights reflect both the informational content and the removal effect of each criterion in a balanced manner.

$$w_j = \frac{w_j^C \times w_j^M}{\sum_{j=1}^{n} w_j^C \times w_j^M}. \tag{19}$$

Stage 3:

The CoCoSo method, originally developed by Yazdani et al. (2018) , is a recent multi-criteria MCDM technique. The computational procedure can be summarized as follows.

The normalized value s_{ij}^{Co} for benefit and cost criteria are obtained as in Eq. (20) and (21), respectively.

$$s_{ij}^{Co} = \frac{s_{ij} - \min_i s_{ij}}{\max_i s_{ij} - \min_i s_{ij}}; \tag{20}$$

$$s_{ij}^{Co} = \frac{\max_i s_{ij} - s_{ij}}{\max_i s_{ij} - \min_i s_{ij}}. \tag{21}$$

In this step, the sum of the weighted comparability sequences (*M*) and the power-weighted comparability sequence (*N*) for each alternative A_i are obtained through Eq. (22) and (23) respectively.

$$M_i = \sum_{j=1}^{n} \left(w_j s_{ij}^{Co} \right); \tag{22}$$

$$N_i = \sum_{j=1}^{n} \left(s_{ij}^{Co} \right)^{w_j}. \tag{23}$$

For each alternative, three utility functions are computed via Eqs. (24)–(26).

$$u_{i1} = \frac{M_i + N_i}{\sum_{i=1}^{m} \left(M_i + N_i \right)}; \tag{24}$$

$$u_{i2} = \frac{N_i}{\min_i N_i} + \frac{M_i}{\min_i M_i}; \tag{25}$$

$$u_{i3} = \frac{\lambda \left(N_i \right) + \left(1 - \lambda \right) \left(M_i \right)}{\lambda \max_i N_i + \left(1 - \lambda \right) \max_i M_i}, \quad 0 \le \lambda \le 1. \tag{26}$$

The traditional CoCoSo method focuses primarily on utility values and does not account for the relative rankings derived from utility distribution. To address this limitation, the present study incorporates the Borda count method to determine the final ranking of alternatives. This approach integrates both the ranking positions and the performance values of alternatives, thereby providing a more comprehensive and balanced evaluation. The normalized values are computed through Eq. (27):

$$t_{iq} = \frac{u_{iq}}{\sqrt{\sum_{i=1}^{m} u_{iq}^2}}, \tag{27}$$

where $q = 1,2,3$.

The final performance value of an alternative A_i, based on the Borda rule (Lin et al., 2020), is defined in Eq. (28):

$$z_i = t_{i1} \frac{m - g_{i1} + 1}{m(m+1)/2} + t_{i2} \frac{m - g_{i2} + 1}{m(m+1)/2} + t_{i3} \frac{m - g_{i3} + 1}{m(m+1)/2}, \tag{28}$$

where T_{i1}, T_{i2}, T_{i3}, and g_{i1}, g_{i2}, g_{i3} are the performance values and ranking from three utility functions $u_{i1}, u_{i2} u_{i3}$ respectively.

4. Empirical example

This section presents the empirical case study and emphasizes the main findings.

4.1. Case overview

Company M is a beauty technology company dedicated to revolutionizing the beauty and wellness industry. The company allocates around 40% of its annual marketing budget to influencer partnerships, with a strategic focus on influencers to enhance brand visibility and drive user engagement. These marketing expenditures are primarily directed towards influencer collaborations on platforms such as Instagram and TikTok. Given this emphasis, it is crucial for the company to adopt a MCDM method in selecting the most suitable influencers, in order to maximize the outcomes of its marketing efforts.

A comprehensive literature review was first conducted to identify factors relevant to influencer selection. To complement this, consultations were held with three DMs: a marketing lead, a project manager, and an experienced digital marketer, denoted by $D = \{D_1, D_2, D_3\}$. The selection of DMs is guided by Bulut and Duru (2018) and Chakrabortty et al. (2023). Based on insights from both the literature and discussions with DMs, seven evaluation criteria were determined to be particularly relevant to the context of Company M, represented by $C = \{C_1, C_2, ..., C_7\}$. These criteria are presented in Table 3. Furthermore, three potential influencers were shortlisted for subsequent analysis.

Table 3. Criteria list

Code	Criteria	Type	Definition	References
C_1	Reputation	Benefit	How positively they're viewed by their audience and the public	Gong et al. (2022)
C_2	Trust-worthiness	Benefit	The degree to which followers believe in the influencer's honesty, transparency and authenticity	Chiu et al. (2024)
C_3	Expertise	Benefit	The influencer's knowledge and skill level in their specific area	Chen et al. (2024), Thuy et al. (2024)
C_4	Popularity	Benefit	The number of followers or fans the influencer has	Gong et al. (2022), Chen et al. (2024)
C_5	Brand fit	Benefit	How well the influencer aligns with the brand or product	Qian and Park (2021), Zhang et al. (2025)
C_6	Social activity	Benefit	The level of engagement and interaction the influencer has with their audience	Ping et al. (2023)
C_7	Endorsement record	Benefit	The influencer's history of brand partnerships and outcomes of past endorsements	Y.-R. Pan et al. (2025)

4.2. Data aggregation

The evaluations provided by DMs are transformed into BPAs according to Eq. (1), as summarized in Table 4. For example, consider the evaluation of alternative A_1 with respect to criteria C_1 by DM D_1. Owing to uncertainty, DM is hesitant between the levels "Medium" and "High" without specifying a strict preference for either. Consequently, the full belief mass is assigned to subset (M, H). The remaining levels are assigned a value of 0 due to the absence of any allocated belief.

Table 4. DMs' assessments

		DM	Significance levels								
			m(VL)	m(L)	m(M)	m(H)	m(VH)	m(L, M)	m(M, H)	m(H, VH)	m(L, M, H)
A_1	C_1	D_1	0	0	0	0	0	0	1	0	0
		D_2	0	0	0	1	0	0	0	0	0
		D_3	0	0	0	0.5	0.5	0	0	0	0
	C_2	D_1	0	0	0	1	0	0	0	0	0
		D_2	0	0	0	0	0	0	0	0	1
		D_3	0	0	0	0	1	0	0	0	0
	⋮						⋱				⋮
	C_7	D_1	0	0	0	1	0	0	0	0	0
		D_2	0	0	1	0	0	0	0	0	0
		D_3	0	0	0.2	0.8	0	0	0	0	0
A_2	C_1	D_1	0	0	1	0	0	0	0	0	0
		D_2	0	0	0	0	0	0	0	1	0
		D_3	0	0	0	1	0	0	0	0	0
	C_2	D_1	0	0	0	0	1	0	0	0	0
		D_2	0	0	0	1	0	0	0	0	0
		D_3	0	0	0	0	1	0	0	0	0
	⋮						⋱				⋮
	C_7	D_1	0	0	1	0	0	0	0	0	0
		D_2	0	0.3	0.7	0	0	0	0	0	0
		D_3	0	0	0	0	0	0	1	0	0
A_3	C_1	D_1	0	0	1	0	0	0	0	0	0
		D_2	0	0	1	0	0	0	0	0	0
		D_3	0	0	0	0	0	0	1	0	0
	C_2	D_1	0	0	0	0	0	0	1	0	0
		D_2	0	0	1	0	0	0	0	0	0
		D_3	0	0	0	1	0	0	0	0	0
	⋮						⋱				⋮
	C_7	D_1	0	0	0	0	0	1	0	0	0
		D_2	0	1	0	0	0	0	0	0	0
		D_3	0	0	0	0	0	1	0	0	0

The BPAs obtained from different DMs are merged using Murphy's combination rule, as expressed in Eqs. (2)–(4). To illustrate the computation process, take the evaluation of alternative A_1 with respect to criteria C_1 as an example. First, the equations are applied to compute the average BPAs corresponding to each significance level through Eq. (2). The results are as follows:

$$\overline{m_{ij}}\left(H\right)=\left(1+0.5\right)/3=0.5;$$

$$\overline{m_{ij}}\left(\mathrm{VH}\right)=0.5/3=0.167;$$

$$\overline{m_{ij}}\left(M,H\right)=1/3=0.333;$$

$$\overline{m_{ij}}\left(VL\right)=\overline{m_{ij}}\left(L\right)=\overline{m_{ij}}\left(M\right)=\overline{m_{ij}}\left(L,M\right)=\overline{m_{ij}}\left(H,VH\right)=\overline{m_{ij}}\left(L,M,H\right)=0.$$

Second, the averaged BPAs are combined with themselves h – 1 = 2 times. In the first iteration, the conflict level is calculated according to Eq. (4) as follows:

$$k_{ij}=0.5\times0.167+0.167\times0.5+\ldots+0.5\times0.333=0.278.$$

In this step, if the traditional Dempster-Shafer rule is used, the conflicting opinions of D_1 and D_2 regarding the performance of A_1 under C_7 cannot be aggregated because their conflict is equal to 1. This highlights the effectiveness of Murphy's combination rule in this study.

Third, combined BPAs are obtained through Eq. (3):

$$m_{ij}^{Mu}\left(H\right)=\left(0.5\times0.5+0.5\times0.333+0.333\times0.5\right)/\left(1-0.278\right)=0.808;$$

$$m_{ij}^{Mu}\left(VH\right)=\left(0.167\times0.167\right)/\left(1-0.278\right)=0.385;$$

$$m_{ij}^{Mu}\left(M,H\right)=\left(0.333\times0.333\right)/\left(1-0.278\right)=0.154;$$

$$m_{ij}^{Mu}\left(VL\right)=m_{ij}^{Mu}\left(L\right)=m_{ij}^{Mu}\left(M\right)=m_{ij}^{Mu}\left(L,M\right)=m_{ij}^{Mu}\left(H,VH\right)=m_{ij}^{Mu}\left(L,M,H\right)=0.$$

The second iteration proceeds in the same manner, yielding the updated values of m_{ij}^{Mu}. The combined BPAs are shown in Table 5.

Table 5. Combined BPAs

		Significance levels								
		m(VL)	m(L)	m(M)	m(H)	m(VH)	m(L, M)	m(M, H)	m(H, VH)	m(L, M, H)
A_1	C_1	0	0	0	0.973	0.002	0	0.026	0	0
	C_2	0	0	0	0.882	0.059	0	0	0	0.059
	$\vdots$					$\ddots$				$\vdots$
	C_7	0	0	0.165	0.835	0	0	0	0	0
A_2	C_1	0	0	0.059	0.882	0	0	0	0.059	0
	C_2	0	0	0	0.059	0.941	0	0	0	0
	$\vdots$					$\ddots$				$\vdots$
	C_7	0	0	0.981	0	0	0	0.019	0	0
A_3	C_1	0	0	0.988	0	0	0	0.012	0	0
	C_2	0	0	0.484	0.484	0	0	0.032	0	0
	$\vdots$					$\ddots$				$\vdots$
	C_7	0	0.802	0	0	0	0.198	0	0	0

Equation (5) is adopted to convert BPAs into probabilities of each significance level. For example, the performance of alternative A_1 with respect to criteria C_1 is calculated as follows:

$$BetP(H) = 0.973/1 + 0.026/2 + 0/2 + 0/3 = 0.986;$$

$$BetP(VH) = 0.002/1 = 0.002;$$

$$BetP(M) = 0/1 + 0.026/2 = 0.013;$$

$$BetP(VL) = BetP(L) = 0.$$

The crisp scores are computed using Eq. (6). The computation process for alternative A_1 under criteria C_1 is presented as follows:

$$s_{11} = 1 \times 0 + 2 \times 0 + 3 \times 0.013 + 4 \times 0.986 + 5 \times 0.002 = 3.989.$$

The remaining crisp values are calculated in the same manner, and the resulting decision matrix is constructed, as shown in Table 6.

Table 6. Decision matrix

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
A_1	3.989	4.000	4.882	2.676	3.853	4.853	3.835
A_2	3.971	4.941	2.941	2.099	3.794	4.901	3.009
A_3	3.006	3.500	2.118	5.000	3.500	5.000	2.099

4.3. Determine criteria weights

First, the CRITIC method is applied to derive the criteria weights based on both variability and correlation. The normalized values s_{ij}^C are computed using Eqs. (7) and (8). Subsequently, the standard deviation is calculated according to Eq. (10), and the results are summarized in Table 7.

Table 7. Standard deviation

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
σ_j	0.572	0.508	0.513	0.529	0.536	0.510	0.500

Through the Eq. (9), the correlation coefficients between the criteria are obtained. The index Q_j and the corresponding criteria weights w_j^C from CRITIC method are computed using Eqs. (11) and (12). The results are illustrated in Table 8.

Table 8. Index and weights

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Q_j	2.607	3.008	2.248	4.499	2.192	4.989	1.971
w_j^C	0.121	0.140	0.104	0.209	0.102	0.232	0.092

Second, the MEREC method is applied to calculate the criteria weights based on the removal effect. The normalized values s_{ij}^{M} are obtained using Eqs. (13) and (14). The performance of each alternative is then evaluated according to Eq. (15). After removing each criterion, the performance of the alternatives is computed using Eq. (16), and the results are presented in Table 9.

Table 9. Performance values after removal

Alternative	C_1 removed	C_2 removed	C_3 removed	C_4 removed	C_5 removed	C_6 removed	C_7 removed
A_1	0.493	0.523	0.373	0.501	0.530	0.549	0.425
A_2	0.318	0.302	0.306	0.384	0.365	0.381	0.298
A_3	0.262	0.262	0.262	0.010	0.262	0.254	0.262

The removing effect E_j and the corresponding weights based on the MEREC method are obtained using Eqs. (17) and (18). The results are presented in Table 10.

Table 10. Removal effects and weights

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
E_j	0.121	0.108	0.253	0.300	0.037	0.010	0.209
w_j^M	0.117	0.104	0.244	0.289	0.036	0.010	0.201

Finally, the final weights obtained from the two methods are calculated using Eq. (19), and the results are presented in Table 11. C_4 emerges as the most important criterion, followed by C_3 and C_7, respectively.

Table 11. Final weights

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
w_j	0.102	0.104	0.183	0.435	0.026	0.016	0.133

4.4. Rank influencers using the improved CoCoSo method

The normalized matrix is obtained through Eqs. (20) and (21). The weighted comparability sequence and the power-weighted comparability sequence for each alternative are computed through Eqs. (22) and (23), respectively. The utility functions are calculated using Eqs. (24)–(26), where $\lambda = 0.5$ as suggested by Yazdani et al. (2018). The results are shown in Table 12.

Table 12. Utility values

Alternative	u_1	u_2	u_3
A_1	0.412	4.289	0.952
A_2	0.418	3.847	0.966
A_3	0.170	2.268	0.391

The normalized values are obtained through Eq. (27). Final performance values based on Borda rule are obtained via Eq. (28), as shown in Table 13. It can be concluded that A_2 is the best choice, followed by A_1 and A_3. The findings indicate that influencer A_2 emerges as the optimal candidate for the company's online marketing campaign, with influencer A_1 ranking as the second-best alternative.

Table 13. Alternative performance

Alternative	z_i	Rank
A_1	1.592	2
A_2	1.783	1
A_3	0.307	3

4.5. Robustness analysis

In this subsection, robustness tests are performed to assess the reliability of the proposed model. The proposed method is first compared with several well-established MCDM ranking methods, including VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), COmplex PRoportional ASSessment (COPRAS), Simple Additive Weighting (SAW), Additive Ratio ASsessment (ARAS), and Weighted Aggregated Sum Product ASsessment (WASPAS), to validate its robustness. As shown in Figure 2, the results of the proposed method are consistent with six out of the seven comparison methods. In the TOPSIS method, the rankings of A_1 and A_2 are reversed, likely due to the similarity in their performance scores.

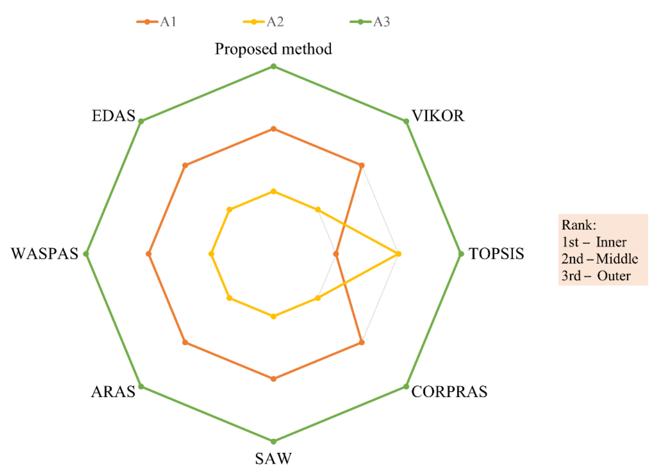

Figure 2. Comparison of ranking results with other MCDM methods

In addition, a sensitivity analysis is conducted to examine the robustness of the results under different values of λ, as shown in Figure 3. The figure demonstrates that the ranking of the alternatives remains unchanged under different values of λ.

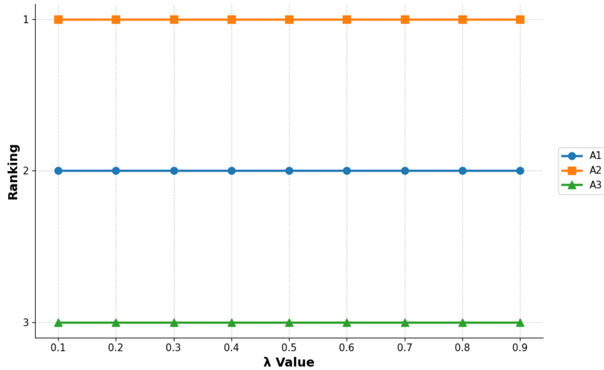

Figure 3. Ranking under different λ values

Moreover, rank reversal is a well-documented issue in MCDM ranking methods, referring to situations in which the relative ranking of alternatives changes when an alternative is either introduced into or removed from the decision set (Mukhametzyanov, 2023). As illustrated in Table 14, the relative ordering of the alternatives remains stable across three scenarios in which one alternative is excluded from the analysis.

Table 14. Rank reversal analysis

Scenarios	A_1 removed	A_2 removed	A_3 removed
Scores	A_2 (2.720) > A_3 (0.839)	A_1 (2.710) > A_3 (0.855)	A_2 (1.882) > A_1 (1.659)

5. Discussion

This section elaborates on the theoretical and practical implications of the study.

5.1. Theoretical implications

This study provides several important theoretical contributions to the literature. First, selecting suitable influencers represents a critical decision for companies, as appropriate choices can generate substantial marketing benefits, whereas inappropriate selections may lead to unfavorable or even detrimental outcomes. To address this challenge, this study establishes a comprehensive evaluation framework for influencer selection, enabling marketers to make more accurate and systematic decisions under conditions of uncertainty. The proposed method offers several advantages over existing models, as summarized in Table 15. By integrating Dempster-Shafer theory within the CoCoSo framework, the approach effectively captures expert hesitancy and handles diverse perspectives of DMs. Moreover, the absence of an appropriate aggregation method for utility functions and an effective weighting scheme results in the mistaken selection of the suboptimal alternative $A_{1,}$ as demonstrated in Table 16.

Second, this study contributes to the influencer marketing literature by demonstrating that influencer selection should be conceptualized as a structured multi-criteria decision-making problem. This perspective extends previous studies that emphasize the strategic importance of influencer selection (Aw & Agnihotri, 2024; Leung et al., 2022) by providing a systematic

Table 15. Proposed model's advantages

Model	Consider criteria's data variability	Consider criteria's correlation	Consider removing effect	Consider DMs' hesitancy	Consider DMs' inconsistency
Traditional CoCoSo	No	No	No	No	No
CRITIC-CoCoSo	Yes	Yes	No	No	No
MEREC-CoCoSo	No	No	Yes	No	No
Proposed method	Yes	Yes	Yes	Yes	Yes

Table 16. Model comparison

	Traditional CoCoSo		CRITIC-CoCoSo		MEREC-CoCoSo		Entropy-CoCoSo		LOPCOW-CoSoSo		Proposed method	
	z_i	g_i	z_i	g_i	z_i	g_i	z_i	g_i	z_i	g_i	z_i	g_i
A_1	2.464	1	2.004	1	2.172	1	2.568	1	2.602	1	1.592	2
A_2	2.139	2	1.328	2	1.258	2	1.887	2	2.447	2	1.783	1
A_3	1.071	3	0.332	3	0.281	3	1.218	3	1.144	3	0.307	3

decision-support framework. Furthermore, the proposed framework addresses the research gap identified by M. Pan et al. (2025), who highlighted the need for more rigorous analytical approaches to influencer selection. Third, this study contributes to the MCDM literature by demonstrating how evidence theory, hybrid objective weighting, and compromise ranking can be integrated into a unified decision-support framework. Consequently, this study extends the application of MCDM techniques to influencer marketing, where their use remains relatively limited. Furthermore, the applicability of the proposed model is not confined to influencer marketing. The methodological framework also demonstrates strong potential for extension to other domains such as safety management, healthcare decision-making and risk assessment.

5.2. Practical applications

The results of this study yield several important and actionable insights for marketing practitioners. In today's fragmented digital ecosystem, the selection of suitable influencers has become a critical determinant of campaign success as consumer attention is limited and brand authenticity is increasingly important. However, marketers often face uncertainty and inconsistency when evaluating influencer performance, especially when relying on subjective judgments. For instance, uncertainty regarding the authenticity of followers may hinder DMs from forming reliable assessments of influencer effectiveness. The proposed decision-making framework provides a mechanism to address such ambiguity, thereby improving the reliability of influencer evaluation outcomes.

Furthermore, the results indicate that C_4 (Popularity) is the most influential criterion in the influencer selection process. Nevertheless, marketers should remain cautious about artificially inflated follower counts, as some influencers purchase fake followers to enhance their perceived influence and financial returns. Although such followers may contribute to perceived popularity (Zhou et al., 2023), they do not represent genuine consumers. Therefore, organizations are encouraged to adopt technical tools and analytical techniques to detect fake followers in influencers' social media accounts, as suggested in Cresci et al. (2015) and Javed et al. (2025). Moreover, C_3 (Expertise) is a key evaluation criterion, particularly when popularity-based indicators are unreliable (Zhou et al., 2023). This finding also supports previous research emphasizing the importance of influencer expertise in shaping consumer responses (Chen et al., 2024; Thuy et al., 2024), while extending the literature by showing how expertise can be systematically incorporated into a comprehensive MCDM evaluation framework. Organizations should conduct interviews with influencers to evaluate their knowledge of the endorsed products. Based on this assessment, companies may also provide training to equip influencers with the necessary product knowledge and communication strategies. Such preparation can significantly enhance customer engagement and purchase intentions (AlFarraj et al., 2021). Therefore, expertise should be viewed as a dynamic capability that can be developed rather than a fixed attribute. In addition, marketers are recommended to request influencers' endorsement records (C_7) to verify their experience and achievements in brand promotion. Moreover, based on the empirical results, since $A_2 > A_1 > A_3$, influencer A_2 should be prioritized for partnership first. If influencer A_2 is unavailable, influencer A_1 can be considered as another option. In contrast, influencer A_3, with a much lower final score, should be avoided, as partnering with this influencer may lead to financial loss or reputational damage for the brand.

Finally, although the proposed framework allows DMs to express uncertainty in their evaluations, it remains essential to collect accurate and reliable data to ensure effective decision outcomes. Furthermore, due to the relatively high computational complexity of the proposed framework, practitioners are advised to focus on the most relevant evaluation criteria and the most promising influencer candidates when applying the model in practice. This approach can streamline the analytical process while maintaining the effectiveness of the decision-making framework. Moreover, it is critical to inform decision-makers about how to provide their judgments. In this model, hesitation is accepted; therefore, it is important to make DMs aware of this flexibility when expressing their evaluations. Furthermore, software applications such as Excel or MATLAB can be used to perform the analytical computations required in the proposed methodology.

6. Conclusions

This study developed an integrated decision-support framework for influencer selection that combines Dempster-Shafer with the CoCoSo method, Murphy's combination rule, hybrid CRITIC–MEREC weighting and the Borda rule. Practically, the framework offers marketers a structured, transparent, and data-driven tool for selecting suitable influencers. Furthermore, the study provides insights into influencer selection practices.

While this study offers significant theoretical and practical contributions, several limitations open avenues for further investigation. First, the validation of the proposed framework was restricted to a single case study in the beauty industry, which limits the scope of empirical generalization. Future research could further validate the proposed framework by applying it to organizations from different industries and business contexts to examine its robustness and generalizability. In addition, studies involving larger and more diverse groups of decision-makers could provide further evidence of the framework's stability and effectiveness in supporting group decision-making under varying levels of uncertainty. Second, the current framework primarily depends on static expert assessments and predefined quantitative metrics. Incorporating dynamic data sources, such as real-time social media analytics and sentiment analysis, could enhance the model's responsiveness and precision in rapidly changing digital ecosystems. Third, the model can be integrated with fuzzy logic to capture both vagueness and uncertainty in the DMs' assessments. Finally, extending the framework from a one-time influencer selection tool to a longitudinal model would substantially increase its managerial utility.

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Author contributions

James J. H. Liou: Conceptualization, Methodology, Supervision, Writing – review & editing. Thanh Tuong Vo: Data curation, Formal analysis, Writing – original draft, Visualization.

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