MÜHENDİSLİK ve DOĞA BİLİMLERİ FAKÜLTESİ

Uluslararası Mühendislik Araştırma ve Geliştirme Dergisi
International Journal of Engineering Research and Development

UMAGD, (2024) 16(1), 373-382.

10.29137/umagd.1398580

Cilt/Volume:16 Sayı/Issue:01 Ocak/January 2024

Araştırma Makalesi / Research Article

A Novel Robust Theoretical Approach on Social Media Advertisement Platform Selection

Sosyal Medya Reklam Platformu Seçimi için Yeni Bir Dayanıklı Teorik Yaklaşım

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Başvuru/Received: *01/12/2023* ***Kabul / Accepted:*** *03/01/2024* ***Çevrimiçi Basım / Published Online:*** *31/01/2024*
Son Versiyon/Final Version: *31/01/2024*

Abstract
Social media advertisement is one of the hottest topics of marketing. This study aims to investigate the selection of social media advertising platforms with a worst-case analysis. In this scope, we propose a novel fuzzy multi-criteria decision making (MCDM) approach based on the robust portfolio optimization framework. We call it the Robust Theoretical Fuzzy Evaluation System (R-FES). We use a case study in the literature to demonstrate R-FES and compare its results with Fuzzy VIKOR's results. We find with R-FES that the social media advertisement budget should be allocated almost equally. We also find that Spearman's rank correlation of Fuzzy VIKOR and R-FES results equals -0.5643. That is, they give very different rankings. We emphasize that these results are specific to the case study and thus can not be generalized.

Key Words
"Advertisement, Fuzzy set, Multi-criteria decision making, Robust optimization, Social media, VIKOR"

Öz
Sosyal medya reklamları pazarlamanın en sıcak gündem maddelerinden biridir. Bu çalışma, sosyal medya reklam platformu seçimini en kötü durum analizi ile incelemeyi amaçlamaktadır. Bu kapsamda, dayanıklı portföy optimizasyon çerçevesini temel alan yeni bir bulanık çok kriterli karar verme (ÇKKV) yaklaşımı önerilmiştir. Bu yaklaşım Dayanıklı Teorik Bulanık Değerlendirme Sistemi (R-FES) olarak adlandırılmıştır. R-FES'i tanıtmak ve sonuçlarını Bulanık VIKOR'un sonuçlarıyla karşılaştırmak için literatürdeki bir vaka çalışması kullanılmıştır. R-FES ile sosyal medya reklam bütçesinin neredeyse eşit şekilde dağıtılması gerektiği bulunmuştur. Ayrıca Bulanık VIKOR ve R-FES sonuçlarının Spearman'ın sıra korelasyonunun -0,5643'e eşit olduğu bulunmuştur. Yani bunların çok farklı sıralamalar verdiği görülmüştür. Bu sonuçlar örnek olaya özgüdür ve bu nedenle genellenemez.

Anahtar Kelimeler
"Reklam, Bulanık Küme, Çok Kriterli Karar Verme, Dayanıklı Optimizasyon, Sosyal Medya, VIKOR"

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1. Introduction

The ongoing development of digital communication technologies and technical innovations influence businesses' marketing strategies. In this regard, social media advertising platforms provide businesses many benefits, including interacting directly with customers and raising brand awareness (Kaplan & Haenlein, 2011; Li & Bernoff, 2008). Today's marketers have many options to create innovative and unique promotional campaigns because of the ongoing development of technology and communication tools. With the benefits of the online environment, the internet's growing dominance has made marketers' attempts to interact with customers and raise brand awareness even more successful (Stefko et al., 2013). Social media platforms present various options for reaching customers with diverse content and interacting with businesses' target audiences (Straker et al., 2015). With billions of individuals visiting them daily, social media platforms give businesses a special opportunity to connect with potential clients.

Global usage statistics for social media platforms today show that these channels must be used efficiently for businesses to reach their target audiences and build brand awareness. For example, 59.4% of internet users globally, or 4.76 billion individuals, actively use social media (Dateportal, 2023). This information highlights how social media gives firms direct access to their target markets.

Daily usage patterns in social media networks attract attention. Globally, users of these platforms spend 2.5 hours a day on average (Dateportal, 2023). This emphasizes how crucial it is for companies to use social media tactics to interact and successfully reach potential clients. Social media will inevitably play a significant role in business marketing in this environment. Modern marketing techniques are built on social media presence, brand awareness building, product promotion and direct consumer communication (Hawkins & Vel, 2013).

A proper advertising budget and a well-thought-out expenditure plan are necessary for social media initiatives to be effective. Businesses must carefully evaluate their advertising strategy and efficiently manage their budgets due to the rise in advertising expenditures and the severity of competition (Berry, 2021). The amount that companies should spend on advertising on social media platforms has now become a matter that marketing teams continuously consider. Businesses have made investments in social media platforms a strategic priority, as evidenced by the $17.5 billion spent by companies on social media advertising in 2022. Social media advertising spending is predicted to reach $51.8 billion by 2027 (Market Research Report, 2023), indicating that this trend will likely continue. Thus, businesses can obtain a competitive edge by carefully preparing social media strategies and allocating advertising funds.

The social media advertisement platform selection problem is an MCDM problem. This study aims to examine this problem with a worst-case analysis. Thus, we propose a novel fuzzy MCDM approach based on the robust portfolio optimization framework given by Lutgens and Schotman (2010). We call this approach the Robust Theoretical Fuzzy Evaluation System (R-FES). The originality of this study is due to the proposed approach. The proposed approach is worst-case-oriented like the game-theoretical approach proposed by Göktaş and Gökerik (in press). The differences between these approaches are that R-FES guarantees a unique solution and depends on a convex optimization problem, whereas the game-theoretical approach does not guarantee a unique solution and depends on a linear optimization problem. This study's primary motivation is to bring innovation in science by integrating the known concepts in robust portfolio optimization into MCDM. There are also many studies on the social media platform selection problem, such as Tavana et al. (2013), Saçan and Tamer (2021), Sudipa et al. (2020), Yücenur et al. (2022), Çalık (2020), Enyinda et al. (2018). We take Fuzzy VIKOR used by Çalık (2020) as a benchmark method and use the data given by Çalık (2020).

The rest of the paper is organized as follows. Section 2 mentions the conceptual framework for social media advertisement platform selection. Section 3 forms the theory of the proposed fuzzy MCDM approach (R-FES). Section 4 illustrates R-FES and compares its results with the results of Fuzzy VIKOR using the data given by Çalık (2020). Section 5 concludes the paper.

2. Conceptual Framework

Social media is defined as an internet-based application emerging on the foundation of Web 2.0, allowing users to share and modify user-generated content, including weblogs, social blogs, microblogs, podcasts, photos, videos, ratings and social bookmarks (Kaplan & Haenlein, 2010; Ismail, 2017). This explanation illustrates how different types of material coexist on social media networks. Social media stands out among the social tools that enable user interaction, material exchange and cooperation (Erkan & Evans, 2016). Well-known sites where related lifestyle groups exchange material are Twitter, Facebook, YouTube and Instagram (Lee et al., 2018; Gökerik et al., 2018).

Marketing managers now consider social media a widely acknowledged and valued essential component of digital marketing strategies (Iankova et al., 2019). Social media users are eager to produce content, build online brand communities and share experiences with friends and followers via tweets, shares, likes and reviews (Jacobson et al., 2020). These days, there is a noticeable surge in social media usage, blogs, podcasts and weblogs for marketing among businesses. Social media is the leading tool marketers use to accomplish various goals, including public relations, sales promotions, branding, CRM and advertising. Marketing managers can benefit from several strategies when strategically employing social media advertising for branding and brand recognition (Kumar et al., 2022). According to Alwagait et al. (2015), social media platforms are web-based tools that facilitate the organization and sharing of user-generated content. By enabling communication between clients and companies, these platforms support the co-creation of value (Dessart, 2017). Nevertheless, it is still being determined from present research which platform customers may choose for business interactions and how value co-creation might vary on each one (Pelletier et al., 2020).

In the evolving digital marketing landscape, the significance of social media advertising platforms is paramount, highlighted by their ability to reshape traditional marketing strategies. These platforms are crucial conduits for interactive and dynamic engagement, enabling businesses to effectively reach and influence their target audiences. The multifaceted nature of social media advertising allows for a more personalized approach to marketing communications, fostering community building and enhancing brand awareness and loyalty. Recent studies affirm the transformative role of social media in digital marketing. Wibowo et al. (2020) elucidate how the advertising value and brand awareness on social media platforms like Facebook significantly influence consumer buying interest, both directly and through the flow experience. This underscores the effectiveness of social media marketing in capturing consumer attention and shaping purchasing decisions. Similarly, Das (2022) highlights the utility of social media marketing in enabling organizations to communicate with existing and potential customers effectively while utilizing data analytics tools to monitor campaign effectiveness. This dual capability of communication and measurement is critical to the success of digital marketing strategies.

The research by Bandara (2020) demonstrates the positive influence of social media advertising on consumer buying behavior in the fast fashion industry. Factors like entertainment, familiarity, and social imaging on platforms such as Instagram significantly influence consumer decisions. This finding is indicative of the power of social media platforms in shaping consumer perceptions and actions. Additionally, the study by Yazdani et al. (2022) highlights the importance of user-generated communication on social media, which positively influences brand equity and attitude, further emphasizing the impact of consumer engagement on brand success. In this context, the approach to digital marketing requires a strategic understanding of the nuances of social media platforms. Di Felice et al. (2020) indicate that optimizing digital platforms can significantly improve market performance by enhancing brand awareness, influencing consumer attitudes, and increasing incomes. This optimization involves understanding and leveraging the unique features of each platform to maximize reach and engagement.

Two critical studies emphasize the benefits of social media advertising platforms. Kaplan and Haenlein's study in 2011 on micro-blogging and Li and Bernoff's exploration in 2008 of strategies for succeeding in a world transformed by social technologies serve as fundamental pillars. These advantages are not merely confined to enhancing consumer engagement but also encompass the strategic elevation of brand awareness. The insights gleaned from these studies illuminate how businesses can harness the potential of social media platforms to forge meaningful connections with their audience, thereby transcending conventional marketing boundaries.

In parallel, the advent of data analytics has emerged as a critical linchpin in social media advertising. As businesses navigate the complex digital marketing landscape, data analytics assumes a central role in meticulously assessing and optimizing the effectiveness of advertising strategies. Fan and Gordon's extensive research on social media analytics in 2014 underscores the indispensable nature of data analytics in gauging the success of advertising campaigns. This analytical approach provides businesses with actionable insights into consumer behavior, preferences and the overall impact of their advertising endeavors. Consequently, companies must embrace a data analytics-focused approach, integrating these insights into the very fabric of their advertising strategies. This strategic alignment ensures the resonance of campaigns and a forward-looking adaptation to the ever-evolving dynamics of the digital marketing landscape. The social media landscape is diverse in terms of its dimensions and functionality, filled with rich and varied platforms (Kietzmann et al., 2011).

Today, traditional media advertisements businesses use are shifting towards social media platforms (Lee & Hong, 2016). Businesses allocate a significant portion of their advertising budgets (Duffett, 2015) and increasingly invest in social media ads (Chi, 2011). Social media advertisements, being internet-based, lead customers to different perceptions and experiences when interacting with these ads. This stems from the inherent nature of social media ads, which provide criteria that encourage customers to interact more with the ads (Laroche et al., 2013; Tuten & Solomon, 2017). We determine these criteria below based on Çalık (2020) where the alternatives for social media advertisement platform selection problem are Facebook, LinkedIn, Instagram, Twitter and YouTube.

Length: Long and pointless shares negatively affect readers and do not give the brand or institution any feedback. As a result, it is essential to examine the optimal length of published content accurately.

Content: Social media users can create and share content, including blogs, social networks, wikis and the virtual world.

Popularity: The increasing popularity of social media platforms creates new marketing opportunities for companies.

Analytics & reporting: Unlike traditional marketing methods, social media platforms offer measurable and reportable results.

Security: It is an essential criterion since social media users store and share information.

Cost: Advertisements aim to reach as many customers as possible with as little cost as possible on social media platforms.

Audience: Businesses determine various marketing strategies based on their target audience.

Easy to use: The increasing trend of social media usage brings very encouraging business opportunities. These opportunities are supported by society's easy use of social media platforms.

Customer service: Customer service should promptly respond to, send and receive pertinent messages and requests.

3. Method

Fuzzy MCDM methods are used when the fuzzy numbers form the decision matrix (Chu & Liu, 2009). The proposed fuzzy MCDM approach (R-FES) is used when its elements are triangular fuzzy numbers. Figure 1 graphically shows the triangular fuzzy number membership function (a_1, a_2, a_3) (Ali et al., 2016).

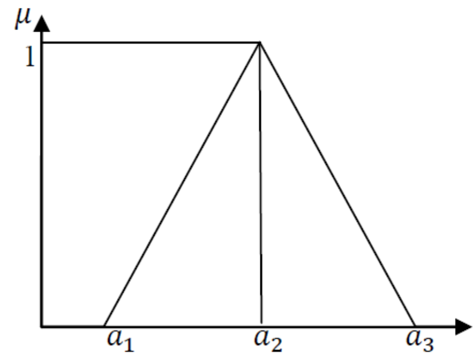

Figure 1. The membership function's graph (Ali et al., 2016).

R-FES brings the opinions of multiple experts together and then gives a unique solution. In this study, we use the linguistic ratings for the expert opinions as in Table 1, adapted from Çalık (2020).

Table 1. Linguistic ratings for alternatives.

Linguistic variables	Corresponding crisp number
Very good (VG)	1
Good (G)	0.75
Fair (F)	0.5
Poor (P)	0.25
Very Poor (VP)	0

We explain the steps of the proposed fuzzy MCDM approach (R-FES) as follows.

Step 1: The chosen experts evaluate each alternative-criterion pair, where Table 1 gives the linguistic ratings.

Step 2: For the i^{th} alternative and j^{th} criterion pair; the minimum rating of expert opinions is assigned as b_{ij}, the median rating of expert opinions is assigned as c_{ij}, the maximum rating of expert opinions is assigned as d_{ij} and the fuzzy utility is determined as the triangular fuzzy number (b_{ij}, c_{ij}, d_{ij}). By bringing them together, a fuzzy decision matrix A_{mxn} is formed. (We assume that there are m alternatives and n criteria.)

Possibility theory is the simplest uncertainty theory. It uses fuzzy sets to determine the possibility distributions (Dubois, 2006). When the possibility distribution is given with the triangular fuzzy number (b_{ij}, c_{ij}, d_{ij}) as in this study, the possibilistic mean and variance are found below, respectively (Göktaş & Duran, 2019). In the calculation of the possibilistic variance, 1 is used instead of d_{ij} to satisfy that the possibilistic variance gives a similar result to a downside risk measure (Göktaş & Güçlü, 2024).

$$\begin{aligned} m_{ij} &=: E_p\left(\left(b_{ij}, c_{ij}, d_{ij}\right)\right) = \frac{b_{ij} + 2c_{ij} + d_{ij}}{4} \\ v_{ij} &:= Var_p\left(\left(b_{ij}, c_{ij}, 1\right)\right) = \left(\frac{1 - b_{ij}}{6}\right)^2 \end{aligned} \tag{1}$$

Step 3: Using the 1^{st} equation in (1), the possibilistic mean matrix $M_{mxn} = (m_{ij})$ is formed.

Step 4: Using the 2nd equation in (1), the possibilistic variance matrix $V_{mxn} = (v_{ij})$ is formed. All elements of M_{mxn} and V_{mxn} are nonnegative.

Let $w = (w_i)$ be the weight vector of m alternatives. For the j^{th} criterion, the possibilistic mean and variance of the portfolio (w) are found below, respectively (Göktaş & Duran, 2019; Göktaş & Güçlü, 2024).

$$\begin{aligned} E_p\left(\sum_{i=1}^{m} w_i\left(b_{ij}, c_{ij}, d_{ij}\right)\right) &= \sum_{i=1}^{m} w_i m_{ij} \\ Var_p\left(\sum_{i=1}^{m} w_i\left(b_{ij}, c_{ij}, 1\right)\right) &= \sum_{i=1}^{m} w_i^2 v_{ij} \end{aligned} \tag{2}$$

Remark: Based on the 2nd equation of (2), we can say that the possibilistic correlation matrix of alternatives' utilities equals the Identity matrix (I) for each criterion. This information corresponds to the situation that asset returns are uncorrelated in portfolio theory. Thus, this information simplifies the results derived by Lutgens and Schotman (2010).

Based on (2), we form the following robust optimization problem where the risk-aversion coefficient (δ) is positive. (3) maximizes the worst-case utility of the portfolio (w) for the different criteria.

$$\max_{w} \min_{j}\left(\sum_{i=1}^{m} w_i m_{ij} - \frac{1}{2}\delta\sum_{i=1}^{m} w_i^2 v_{ij}\right) \tag{3}$$

Due to the definition of the minimum function, (3) and (4) are equivalent problems where y is a variable associated with the worst-case situation. (4) is a strictly concave maximization problem. Thus, it can be solved with CVX, a MATLAB software for convex optimization (Grant & Boyd, 2008).

$$\begin{aligned} &\max y \\ &s.t.\ y - \left(\sum_{i=1}^{m} w_i m_{ij} - \frac{1}{2}\delta\sum_{i=1}^{m} w_i^2 v_{ij}\right) \le 0 \ \ for\ all\ \ j \end{aligned} \tag{4}$$

The optimal solution of (4) for the i^{th} alternative (w_i^*) satisfies the following condition. Here, λ_j is the nonnegative Lagrange multiplier associated with the j^{th} constraint of (4). The sum of the Lagrange multipliers equals 1. δ is just a scaling parameter and does not affect the Lagrange multipliers. See Theorem 1 given by Lutgens & Schotman (2010) for further information. Since m_{ij} and v_{ij} parameters are all nonnegative, w_i^* is also nonnegative.

$$w_i^* = \frac{1}{\delta}\frac{\sum_{j=1}^{n}\lambda_j m_{ij}}{\sum_{j=1}^{n}\lambda_j v_{ij}} \tag{5}$$

Remark: (5) is not an explicit solution of (4) since we do not know the Lagrange multipliers. Special software such as CVX can be used to determine the optimal solution of (4) and the Lagrange multipliers.

Step 5: (4) is solved for δ = 2 to find w_i^* and λ_j values. The weight of the j^{th} criterion is objectively determined as λ_j.

Step 6: The priority of the i^{th} alternative (p_i) is found below. The sum of priorities equals 1. (Since δ is just a scaling parameter, the priority values and criteria weights are independent from δ.)

$$p_i = \frac{w_i^*}{\sum_{i=1}^{m} w_i^*} \tag{6}$$

Step 7: The priority vector $p = (p_i)$ determines the resource allocation to the alternatives and/or ranks the alternatives.

CVX code for the solution of (4) is below when δ = 2 and the Mosek solver is chosen. We see that R-FES can be easily implemented with the MATLAB software CVX.

$$
\begin{aligned}
& cvx\_solver\ mosek \\
& cvx\_begin \\
& variables\ w(m)\ y; \\
& dual\ variable\ \lambda; \\
& \quad maximize\,(y); \\
& \quad subject\ to \\
& \qquad \lambda:\ y*ones(n,1)-\left(transpose(M)*w-transpose(V)*(w.\hat{}\,2)\right) <=\ zeros(n,1); \\
& cvx\_end
\end{aligned} \tag{7}
$$

Remark: We know from the KKT conditions that the weight of the j^{th} criterion (λ_j) is equal 0 when the j^{th} constraint of (4) is not an active constraint. λ_j may be positive only when the j^{th} constraint of (4) is an active constraint.

4. Results and Discussion

This section illustrates R-FES and compares its results with Fuzzy VIKOR's results using the case study given by Çalık (2020). The case study is about social media platform selection for a travel agency in Turkey. The case study has ten experts, five alternatives and nine criteria. The alternatives are A1 (Facebook), A2 (LinkedIn), A3 (Instagram), A4 (Twitter) and A5 (YouTube). The criteria are C1 (length), C2 (content), C3 (popularity), C4 (analytics & reporting), C5 (security), C6 (cost), C7 (audience), C8 (easy to use) and C9 (customer service). We implement R-FES for the case study with the following steps.

Step 1: Ten experts' opinions are taken for each alternative-criterion pair, where Table 1 gives the linguistic ratings. Table 2 shows the first expert's opinion. For example, the first expert's opinion for the A1-C1 pair is Very Good (VG).

Table 2. The first expert's opinions.

	C1	C2	C3	C4	C5	C6	C7	C8	C9
A1	VG	G	G	F	F	P	F	VG	F
A2	F	G	F	VP	F	P	F	G	P
A3	VG	G	VG	VP	G	G	G	G	F
A4	F	P	F	VP	P	F	G	P	F
A5	G	F	F	G	F	G	P	F	P

Step 2: Using the minimum, median and maximum ratings of expert opinions for each alternative-criterion pair, we determine the fuzzy decision matrix (A) elements as in Table 3. For example, the minimum, median and maximum ratings of expert opinions for the A1-C1 pair are Fair (F), Good (G) and Very Good (VG) respectively.

Table 3. The fuzzy decision matrix (A).

	C1	C2	C3	C4	C5	C6	C7	C8	C9
A1	(0.5, 0.75, 1)	(0.25, 0.625, 1)	(0, 0.625, 1)	(0, 0.5, 1)	(0.5, 0.75, 1)	(0, 0.25, 1)	(0, 0.625, 0.75)	(0, 0.5, 1)	(0.5, 0.75, 1)
A2	(0.25, 0.625, 1)	(0.25, 0.625, 1)	(0, 0.625, 1)	(0, 0.375, 1)	(0, 0.5, 0.75)	(0, 0.25, 1)	(0, 0.5, 1)	(0, 0.75, 1)	(0, 0.25, 1)
A3	(0.75, 0.75, 1)	(0, 0.75, 1)	(0, 0.75, 1)	(0, 0.5, 1)	(0.25, 0.5, 1)	(0.5, 0.75, 1)	(0.25, 0.625, 1)	(0, 0.5, 1)	(0, 0.5, 0.75)
A4	(0.25, 0.5, 0.75)	(0, 0.25, 0.75)	(0, 0.375, 1)	(0, 0.5, 1)	(0, 0.25, 1)	(0, 0.5, 1)	(0.25, 0.5, 0.75)	(0, 0.375, 1)	(0, 0.75, 0.75)
A5	(0, 0.25, 0.75)	(0.5, 0.75, 1)	(0, 0.375, 1)	(0, 0.625, 1)	(0, 0.375, 1)	(0, 0.75, 1)	(0, 0.25, 1)	(0, 0.375, 1)	(0, 0.625, 1)

Step 3: Using the 1st equation in (1), we form the possibilistic mean matrix (M) as in Table 4. Here, m_{11} = (0.5+2x0.75+1)/4 = 0.75.

Table 4. The possibilistic mean matrix (M).

	C1	C2	C3	C4	C5	C6	C7	C8	C9
A1	0.7500	0.6250	0.5625	0.5000	0.7500	0.3750	0.5000	0.5000	0.7500
A2	0.6250	0.6250	0.5625	0.4375	0.4375	0.3750	0.5000	0.6250	0.3750
A3	0.8125	0.6250	0.6250	0.5000	0.5625	0.7500	0.6250	0.5000	0.4375
A4	0.5000	0.3125	0.4375	0.5000	0.3750	0.5000	0.5000	0.4375	0.5625
A5	0.3125	0.7500	0.4375	0.5625	0.4375	0.6250	0.3750	0.4375	0.5625

Step 4: Using the 2nd equation in (1), we form the possibilistic variance matrix (V) as in Table 5. Here, $v_{11}=(1-0.5)^2/36= 0.0069$.

Table 5. The possibilistic variance matrix (V).

	C1	C2	C3	C4	C5	C6	C7	C8	C9
A1	0.0069	0.0156	0.0278	0.0278	0.0069	0.0278	0.0278	0.0278	0.0069
A2	0.0156	0.0156	0.0278	0.0278	0.0278	0.0278	0.0278	0.0278	0.0278
A3	0.0017	0.0278	0.0278	0.0278	0.0156	0.0069	0.0156	0.0278	0.0278
A4	0.0156	0.0278	0.0278	0.0278	0.0278	0.0278	0.0156	0.0278	0.0278
A5	0.0278	0.0069	0.0278	0.0278	0.0278	0.0278	0.0278	0.0278	0.0278

Step 5: By solving (4) with the CVX code given in (7), we find that $w_1^* = 8.9996$, $w_2^* = 9.0803$, $w_3^* = 8.9996$, $w_4^* = 8.5982$, $w_5^* = 9.3213$, $\lambda_4 = 0.6429$, $\lambda_8 = 0.3571$ and the other Lagrange multipliers equal 0. R-FES objectively determines the weight of C4 as 0.6429 and the weight of C8 as 0.3571. The weights of other criteria equal 0.

Step 6: Using (6), we determine $p_1 = 0.2$, $p_2 = 0.2018$, $p_3 = 0.2$, $p_4 = 0.1911$ and $p_5 = 0.2071$.

Step 7: We find the ranks of alternatives, which are A5 > A2 > A1 = A3 > A4. In addition, the social media advertisement budget's allocation is A5 = %20.71, A2 = %20.18, A1 = A3 = %20 and A4 = %19.11.

It may be helpful to make a scenario analysis for the case study. Let S0 be the base scenario in which all criteria are considered for the social media platform selection problem. Let S1 be the scenario in which C4 and C8 are omitted from the criteria set. Then, we find that the weight of C3 equals 1 by implementing R-FES. Let S2 be the scenario in which C3, C4 and C8 are omitted from the criteria set. Then, we find that the weights of C7 and C9 are 0.7276 and 0.2724 respectively by implementing R-FES. Let S3 be the scenario in which C3, C4, C7, C8 and C9 are omitted from the criteria set. Then, we find that the weights of C1, C2, C5 and C6 are 0, 0.2013, 0.3737 and 0.4250 respectively by implementing R-FES. We also find the priorities (weights) and ranks of alternatives in each scenario, as in Table 6. R-FES results change based on the criteria set since it determines the worst-case situation for the optimal solution of (4).

Table 6. Scenario analysis for the case study.

	S0		S1		S2		S3	
	Weight	Rank	Weight	Rank	Weight	Rank	Weight	Rank
A1	0.2000	3.5	0.2143	2.5	0.2227	3	0.2387	2
A2	0.2018	2	0.2143	2.5	0.1453	4	0.1312	4
A3	0.2000	3.5	0.2381	1	0.2626	1	0.3371	1
A4	0.1911	5	0.1667	4.5	0.2365	2	0.1108	5
A5	0.2071	1	0.1667	4.5	0.1329	5	0.1822	3

The social media advertisement budget is allocated almost equally with R-FES. This is not a big surprise for us since R-FES is based on robust portfolio optimization, which gives well-diversified optimal portfolios (Lutgens & Schotman, 2010). Fuzzy VIKOR determines the ranks of alternatives as A3 > A1 > A4 > A5 > A2. On the other hand, these ranks change highly with the change in the criteria weights (Çalık, 2020). Thus, we think that the objective criteria weighting is an advantage of R-FES. Fuzzy VIKOR only uses the fuzzy mean and ignores the fuzzy variance (Çalık, 2020). In contrast, R-FES uses the possibilistic mean and variance together. We think that this is another advantage of R-FES. We also find that Spearman's rank correlation of Fuzzy VIKOR and R-FES results equals

-0.5643. That is, they give very different rankings. This may be because the results of Fuzzy VIKOR highly depend on the criteria weights, and R-FES is based on worst-case analysis, unlike Fuzzy VIKOR.

5. Conclusion

In this study, we examine the social media advertising platform selection with the proposed fuzzy MCDM approach (R-FES) for a case study in the literature. With the help of special software, the proposed approach can be easily implemented for any business problem, which can be formalized as an MCDM problem. The proposed approach brings different opinions together. Thus, it may help managers make good decisions if the expert knowledge is high quality. The strengths of the proposed approach are that 1) it gives a unique solution, 2) the information in the fuzzy decision matrix is highly considered using the first two possibilistic moments, and 3) it objectively determines the criteria weights. Its main limitation is that it may not be appropriate for non-conservative decision-makers due to the worst-case orientation. In future research, it can be generalized for different fuzzy numbers than triangular fuzzy numbers. Furthermore, the proposed approach can be used for other MCDM problems.

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