SVNN-Entropy Weighting Strategy (SVNN-EWS) for Popularity Ranking Factors in Library and Information System: a neutrosophic framework

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Abstract

Information Retrieval (IR) in Library and Information System (LIS) is not displayed in their search results as users like to see them in deserved order. It is happening because of the incorporation of a few numbers of ranking factors and the model is not user-centred. Consequently, problems with user satisfaction are continuously reported. There are six groups of ranking factors, namely, "Text Statistics, Popularity, Freshness, Locality and Availability, Content Properties, and User Background". The objectives of the study are to present the factors related to the ranking of search results in LIS, and to assign the weights of each factor of popularity group considering the experts' opinion using the entropy method in Single Valued Neutrosophic Numbers (SVNNs). A review of the concerned literature shows that there exists no such study that used the Entropy strategy in Information Retrieval (IR) in LIS and determine weights of the factors for ordering search results considering popularity ranking factors and on the other hand this is a user-centric approach. All these make the proposed study a novelty approach. The considered factors can be used in designing a ranking model for a LIS, designing Web-scale Discovery Tools (DT), or when discussing such a project with an Integrated Library Management System (ILMS) vendor.

Keywords: Entropy, Information retrieval, Multi criteria decision making, Neutrosophic set, Online public access catalogue, Ranking factors, Relevance ranking, Single-valued neutrosophic number

1. Introduction

The library software helps us to locate all kinds of collections of a traditional library, digital library, e-library, etc. through its Online Public Access Catalogue(OPAC) or web version of that which is known as Web-OPAC. There are so many free and open-source ILMS as well as a number of commercials too. But the search results of OPAC have some shortcomings related to user-centredness and lack of sophistication in presentation (Lewandowski, 2010). Today's Library and Information Systems consider very few factors as well as poor principles and strategies to bring their search results in relevancy order which is why they are producing such poor results (Sahoo & Panigrahi, 2022). The best search results in a ranking done by web search engines may be a very much exemplary model for any other information system like a Library and Information System (LIS) to satisfy users and make the search results ordered maintaining relevancy. Search engine technologies have been used to meet the expectations of users in searching and retrieving information (Antelman, Lynema, & Pace, 2006; Connaway & Dickey, 2010; Breeding, 2006; Niu & Hemminger, 2010). Behnert and Lewandowski (2015) categorise all ranking factors (RF) related to or may be considered for LIS into six groups. Under each group, there are a number of factors that can be considered to rank library materials maintaining the relevancy order of search results. LIS use only a few in their system but for better results, we have to systematically test various factors for the best suited in the system. There exist no specific tools to satisfy all users in all aspects. Therefore, rethinking the factors, analysis of the ranking strategy, new algorithms, new framework are always needed. Anew model is inevitable to achieve a more or less satisfactory level by the trial-and-error method (Sahoo & Panigrahi, 2022). There are a number of popularity factors suitable for LIS but here we have considered only ten (10) broad sub-groups under group popularity to show the practical exposure of how to incorporate those in the system.

Uncertainty involves in every sphere of real-life problems. To handle uncertainty Zadeh (1965) developed the Fuzzy Set (FS). Smarandache (1998) extended the FS to the Neutrosophic Set (NS) which is a generalisation of different types of FSs such as Intuitionistic FS (IFS), etc. Single-Valued NS (SVNS) (Wang et al., 2010) was grounded as a subclass of NS which is more popular in Multi-Criteria Decision Making (MCDM) (Khan et al., 2018) problems. However, fuzzy is concerned with capturing and conveying the vagueness of an abstract concept. Therefore, the reason for applying single-valued neutrosophic is easy to use in information processing and computational simplicity in linguistic preferences. Further Smarandache (2019) established that NS is the generalisation of Pythagorean FS (Yager, 2013), spherical FS (Kutlu Gündoğdu, & Kahraman, 2019), and q-rung orthopair FS (Yager, 2017). Also, Membership Function (MF), non-MF, and indeterminacy MF are independent in NS and NS is capable of dealing with inconsistency and indeterminacy. On the other hand, ranking factors inherently involve uncertainty, indeterminacy, and inconsistency. So, NS has advantages over other extensions of FSs for the present study.

NS was extended to Single Valued Quadripartitioned NS (SVQNS) (Chatterjee et al., 2016), interval quadripartitioned NS (IQNS) (Pramanik, 2022), Pentapartitioned NS (PNS) (Mallick and Pramanik, 2020), Interval PNS (Pramanik, in press) to capture uncertainty in a convincing way. Details of the development of neutrosophic theories and applications have been documented in the studies (Smarandache & Pramanik 2016, 2018; Pramanik, Mallick & Dasgupta, 2018; Peng 2020; Pramanik 2020, 2022).

As the neutrosophic environment is more realistic, we choose the Single Valued Neutrosophic Number (SVNN) environment for the present investigation. In this environment, we combine the entropy strategy and group decision-making. The entropy strategy is used to assign weights to the factors based on the opinions of the subject experts cum users. We apply the SVNN

Weighted Averaging Aggregation (SVNNWAA) operator (Ye, 2014) to aggregate the decision matrices.

In the real world, the DM sprefer to evaluate the importance of attributes in a flexible way by utilising linguistic variables. The reason behind it is the partial knowledge about the criteria, unfamiliar domains, expertise, etc. We have developed the framework based on the opinion of the user (user-centric approach) and SVNS theory which is more capable to reflect reality than the traditional approaches.

2. Review of the literature related to the study

Literature reviews have been done on library materials ranking factors, popularity group ranking factors, SVNS, the process of assigning weights to the criteria, and the entropy strategy. Freshness was the most-used ranking criterion (Lewandowski, 2009) in catalogues. For a real ranking (Dellit & Boston, 2007), OPACs usually employ only standard text matching. Besides text matching, there are some other ideas that may be considered to improve the relevance ranking. Flimm (2007) proposed popularity ranking factors in catalogues for relevance ranking. According to Mercun and Zumer (2008) and Sadeh (2007) ranking search results in the LIS include "circulation statistics, book review data, the number of downloads, and the number of print copies owned by the institutions" (Lewandowski, 2009).

It may happen that users are not interested or they are not able to look through the whole result sets. So, superiority in ranking order reduces to a critical feature (Lewandowski, 2009). Behnert and Lewandowski (2015) categorised all RFs into six groups namely, "text statistics, popularity, freshness, locality & availability, content properties, and user background". Plassmeier et al. (2016) considered citation counts, usage data, and author metrics in their study and also opined that in future studies, all other popularity group factors should be included for a complete relevance model. Bornmann, Mutz, and Daniel (2008) mentioned that the h-index and m-index are more important to reflect the impact of the work of a researcher. The Characteristic Scores and Scales (CSS) strategy helps in finding the characteristic partitions for citation distributions of papers (Glanzel & Schubert, 1988). Plassmeier et al. (2016) stated that "the effectiveness of CSS scores as utilities in the overall relevance model must still be evaluated in user studies".

Various criterion weighting procedures have been established in the literature (Peng, 2020) for the MCDM process such as CRITIC (Diakoulaki et al., 1995), Entropy Weight Method(EWM) (Zou et al., 2006; Liu et al., 2010), maximising deviation method (Wu & Chen, 2007), optimisation method (Wang & Zhang, 2009; Biswas, Pramanik & Giri, 2014). The EWM in the SVNN environment (Majumder & Samanta, 2014) was used by Biswas, Pramanik and Giri (2014) to determine the unknown attribute weights in MCDM problems.

Attia, Gadallah, and Hefny (2014) presented an enhanced multi-view fuzzy IR model based on linguistics. Gupta, Saini, and Saxena (2015) developed the fuzzy ranking function for IR system. Alhabashneh, Iqbal, Doctor, and James (2017) presented the fuzzy-based approach using relevance feedback. Jain, Seeja, and Jindal (2021) presented the fuzzy ontology-based Information Retrieval (IR) framework. Ibrihicha, Oussousb, Ibrihicha, and Esghi (2022) presented a survey on IR basics and discussed the different approaches but did not include the fuzzy and neutrosophic based approaches in their study. Sinha and Kumar (2020) presented a neutrosophic model for Healthcare Information Retrieval (HIR) that was an improvement over the fuzzy models. But it considered only Term Frequency (TF) and Inverse Document Frequency (IDF) as RFs.

It is observed that no research work has been developed to use an entropy strategy for IR model in an SVNN environment to incorporate RFs considered for the relevance ranking of search results in LIS.

3. Objectives of the study

The main objectives are mentioned below:

- to study the feasibility of entropy strategy for SVNN environment in LIS information searching
- to design a framework for calculating weights of the ranking factors in IR using the SVNN-Entropy Weighting Strategy (SVNN-EWS).

4. Methodology

The research has been done using review of the relevant documents to obtain ranking factors under group popularity so far identified and also applicable for LIS searching by researchers. A questionnaire has been prepared to collect the opinions of the experts who are also users of the system. The opinion was collected on five-point Likert scale (see Table 1). All the collected data have been put in the tabulated form and then converted the data into SVNNs. Anew model, namely SVNN-EWS for determining the weights of RFs was devised using neutrosophic weighting technique (Biswas, Pramanik, & Giri, 2016) and the entropy of NSs (Majumdar & Samanta, 2014).

5. Preliminaries of SVNSs (Wang et al., 2010)

An SVNS σ in a universal set Ξ is characterised by a truth MF $\ddot{t}_\sigma(\ddot{x})$, an indeterminacy MF $\ddot{i}_\sigma(\ddot{x})$, and a falsity MF $\ddot{f}_\sigma(\ddot{x})$ with $\ddot{t}(\ddot{x}), \ddot{i}_\sigma(\ddot{x}), \ddot{f}_\sigma(\ddot{x}) \in [0,1], \forall \ddot{x} \in \Xi$.

When, Ξ is continuous, an SVNS σ can be presented as:

$$\sigma = \int_{\ddot{x}} \left\langle \ddot{t}_\sigma(\ddot{x}), \ddot{i}_\sigma(\ddot{x}), \ddot{f}_\sigma(\ddot{x}) \right\rangle / \ddot{x}, \forall \ddot{x} \in \Xi$$

and when Ξ is discrete, an SVNS σ can be presented as:

$$\sigma = \sum \left\langle \ddot{t}_\sigma(\ddot{x}), \ddot{i}_\sigma(\ddot{x}), \ddot{f}_\sigma(\ddot{x}) \right\rangle / \ddot{x}, \forall \ddot{x} \in \Xi$$

with $0 \le \sup \ddot{t}_\sigma(\ddot{x}) + \sup \ddot{i}_\sigma(\ddot{x}) + \ddot{f}_\sigma(\ddot{x}) \le 3, \forall \ddot{x} \in \Xi$

Therefore,

$0 \le \sup \ddot{t}_\sigma(\ddot{x}) + \sup \ddot{i}_\sigma(\ddot{x}) + \ddot{f}_\sigma(\ddot{x}) \le 3$.

For convenience, the triplet

$$\left\langle \ddot{t}_\sigma(\ddot{x}), \ddot{i}_\sigma(\ddot{x}), \ddot{f}_\sigma(\ddot{x}) \right\rangle$$

is called an SVNN and presented as

$$\left\langle \ddot{t}_\sigma, \ddot{i}_\sigma, \ddot{f}_\sigma \right\rangle.$$

Let $\kappa_1 = \langle d_1, e_1, f_1 \rangle$ and $\bar{\kappa}_1 = \langle \bar{d}_1, \bar{e}_1, \bar{f}_1 \rangle$ be any two SVNNs with

$$d_1, e_1, f_1, \bar{d}_1, \bar{e}_1, \bar{f}_1 \in [0,1],$$

$$(d_1 + e_1 + f_1) \in [0,3] \text{ and } (\bar{d}_1 + \bar{e}_1 + \bar{f}_1) \in [0,3]$$

Then, the operations for SVNNs (Broumi et al., 2018) are presented as follows;

i. $\kappa_1 \oplus \bar{\kappa}_1 = \langle d_1 + \bar{d}_1 - d_1\bar{d}_2, e_1\bar{e}_1, f_1 f_1 \rangle$ [Summation] (1)

ii. $\kappa_1 \otimes \bar{\kappa} = \langle d_1\bar{d}_1, e_1 + \bar{e}_1 - e_1\bar{e}_1, f_1 + \bar{f}_1 - f_1\bar{f}_1 \rangle$ [Multiplication] (2)

iii. $ck_1 = \langle 1-(1-d_1)^c, e_1^c, f_1^c \rangle, c > 0$ [Scaler multiplication] (3)

iv. $\kappa_1^c = \langle d_1^c, 1-(1-e_1)^c, 1-(1-f_1)^c \rangle, c > 0$ (4)

6. SVNN -Entropy Weighting Strategy

Formulate a committee of P(≥ 2) DMs. P number of DMs evaluate the alternative Ar (r= 1, 2, …, m), (m ≥ 2) with respect to n criteria F_s(s=1,2,…, n), (n ≥ 2). SVNN-EWS is developed using the following steps (See Fig.1).

Step 1: Construction of the decision matrices

Suppose that $Q^P = (g^P_{rs})_{m\times n}$ is the p[th] decision matrix where information about the alternative A_r is given by the p[th] DM subject to the criterion F_s is a linguistic variable $\tilde{a}^p_{rs}$. This linguistic variable can be transformed into SVNN (see table 1). After converting the linguistic variable into SVNN rating values, the p[th] decision matrix is constructed as follows:

$$G^p = (g^p_{rs})_{m\times n} = \begin{pmatrix} g^p_{11} & g^p_{12} & \cdots & g^p_{1n} \\ g^p_{21} & g^p_{22} & \cdots & g^p_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ g^p_{m1} & g^p_{m2} & \cdots & g^p_{mn} \end{pmatrix} \quad (5)$$

where $g^p_{rs} = \langle a^p_{rs}, b^p_{rs}, c^p_{rs} \rangle$

where p=1, 2, … P., r = 1, 2, …, m & s = 1, 2, …, n

Table 1. Linguistic terms for weighting of attributes and decision makers and rating alternatives (Biswas et al., 2016)

Linguistic terms	SVNNs
Extremely Important (EI)	⟨0.90,0.10,0.10⟩
Very Important (VI)	⟨0.80,0.20,0.15⟩
Important (I)	⟨0.50,0.40,0.45⟩
Very Unimportant (VU)	⟨0.35,0.60,0.70⟩
Extremely Unimportant (EU),	⟨0.10,0.80,0.90⟩

Step 2: Normalise the decision matrices

Normalisation is done using the rule (Biswas et al., 2016) (Eqn. 6)

$$d^p_{rs} = \begin{cases} g^p_{rs}, \text{for benefit critrion} \\ (g^p_{rs})', \text{for cos t criterion} \end{cases} \quad (6)$$

and the matrix G^p is converted into the matrix

$D^p_{rs} = (d^p_{rs})_{m\times n}$ where $(g^p_{rs})' = (c^p_{rs}, 1-b^p_{rs}, a^p_{rs})$ is the complement of SVNN

$g^p_{rs} = \langle a^p_{rs}, b^p_{rs}, c^p_{rs} \rangle$.

Then the normalised decision matrix appears of the form:

$$D^p = \begin{pmatrix} d^p_{11} & d^p_{12} & \cdots & d^p_{1n} \\ d^p_{21} & d^p_{22} & \cdots & d^p_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ d^p_{m1} & d^p_{m2} & \cdots & d^p_{mn} \end{pmatrix}, \text{ p= 1, 2, ..., P.} \quad (7)$$

Step 3: Calculate the weights of the DMs

Assume that $\varphi_p = \langle T_p(\omega), I_p(\omega), F_p(\omega) \rangle$ is rating for the p-th DM. Then, φ_p, weight of the p[th]

$$DM = \frac{1-\sqrt{\{(1-T_p(\omega))^2 + (I_p(\omega))^2 + (F_p(\omega))^2\}/3}}{\sum_{p=1}^{P}(1-\sqrt{\{(1-T_p(\omega))^2 + (I_p(\omega))^2 + (F_p(\omega))^2\}/3})} \quad (8)$$

and $\sum_{p=1}^{P} \varphi_p = 1$ (9)

Step 4: Aggregate the decision matrices

Utilising

$D^p_{rs} = (d^p_{rs})_{m\times n}$, $\varphi = (\varphi_1, \varphi_2, \ldots, \varphi_P)^T$,

$\varphi_p \in [0,1]$ and $\sum_{p=1}^{P} \varphi_p = 1$, the Aggregated Decision Matrix (ADM) *D'* is obtained by employing the SVNWAA operator (Ye, 2014) for SVNNs as follows:

$$\begin{aligned} & SVNWAA_{\varphi}(d_{rs}^{1}, d_{rs}^{2}, \ldots, d_{rs}^{P}) \\ & = \varphi_1 d_{rs}^{1} \oplus \varphi_2 d_{rs}^{2} \oplus \ldots \oplus \varphi_P d_{rs}^{P} \\ & = \left\langle 1-\prod_{p=1}^{P}(1-T_{rs}^{(p)})^{\varphi_p}, \prod_{p=1}^{P}(I_{rs}^{(p)})^{\varphi_p}, \prod_{p=1}^{P}(F_{rs}^{(p)})^{\varphi_p} \right\rangle \end{aligned} \quad (10)$$

The ADM is obtained as:

$$D' = \left(\delta'_{rs}\right)_{m \times n} = \begin{pmatrix} \delta'_{11} & \delta'_{12} & \cdots & \delta'_{1n} \\ \delta'_{21} & \delta'_{22} & \cdots & \delta'_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \delta'_{m1} & \delta'_{m2} & \cdots & \delta'_{mn} \end{pmatrix} \quad (11)$$

where $\delta'_{rs} = \langle T'_{rs}, I'_{rs}, F'_{rs} \rangle$. (12)

Step 5: Determine the weights of the attributes

The entropy value (Majumder & Samanta, 2014) E_S of the s^{th} attribute F_S(s=1, 2, …, n), is obtained using the formula

$$E_s = 1 - \frac{1}{n}\sum_{r=1}^{m}(T'_{rs} + F'_{rs})(I_{rs} - I'_{rs}) \quad (13)$$

For r=1, 2,…, m; s=1, 2,…,n.

The entropy weight (Hwang & Yoon, 1981; Wang & Zhang, 2009) ω_S of the s-th attribute F_S is presented by

$$\omega_s = \frac{1-E_s}{\sum_{s=1}^{n}(1-E_s)} \quad (14)$$

We obtain the weight vector

$$\omega = (\omega_1, \omega_2 \ldots \omega_n)' \text{ with } \omega_s \in [0,1] \text{ and } \sum_{s=1}^{n}\omega_s = 1.$$

Step 6: Rank the attributes

Now finally we obtain the weights of the attributes. The attributes are arranged in descending order.

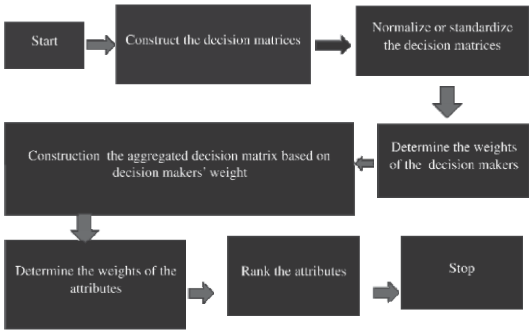

Fig.1: Flowchart of the SVNN-EWS

7. Data, calculations and results

We have considered five experts cum users as decision maker (DM1, DM2 ,DM3, DM4,DM5) in the study. At first, we have elaborately defined the objectives of the study to the experts. Then briefly explained the definition, scope and coverage of all criterion. Five DMs have given their opinion about the importance of each particular ranking factors under the group popularity mentioned in the questionnaire on the basis of five-point Likert scale. The factors are Subject (F1), Circulation (F2), Language (F3), Number of published edition (F4), Number of Copies (F5), Bibliometric Methods (F6), Publisher Authority (F7), Purchasing Behaviour (F8), Ratings (F9) and Enriched Metadata (F10). The factors are related to the documents denoted as A1 , A2 , A3, A4 and we have designed a framework to determine the weights of the attributes. The weights of five DMs may not be the same as far as their status is concerned. In table 1, weights of the DM are expressed in linguistic terms. The importance of each DM is expressed by linguistic terms with its corresponding SVNNs (see table 2). The opinions of the DMs are shown table 3 to table 7.

Table 2: Importance of Decision Makers expressed with SVNNs

Decision Maker (DM)	DM1	DM2	DM3 〈	DM4	DM5 〉 〈
Likert Scale	EI	VI	VI	EI	EI
SVNNs	0.90,0.10,0.10	0.80,0.20,0.15	0.80,0.20,0.15	0.90,0.10,0.10	0.90,0.10,0.10 〉

Table 3: Decision matrix $P^{(1)}$

A_i	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8	F_9	F_{10}
A_1	VI	VI	VI	VI	VI	VI	VI	VI	EI	EI
A_2	EI	VI	I	EI	VI	VI	VI	EI	I	VU
A_3	VI	VI	VI	VU	VI	VU	I	I	I	I
A_4	VI	VI	VI	VI	VI	VI	VU	VU	I	I

Table 4: Decision matrix $P^{(2)}$

A_i	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8	F_9	F_{10}
A_1	VI	VU	I	I	I	I	EI	I	EI	VI
A_2	VI	I	VU	I	VI	VI	VI	I	VI	VI
A_3	I	I	I	VI	VI	I	I	VU	I	VI
A_4	VI	VI	VI	VU	VU	VU	VU	VI	VU	I

Table 5: Decision matrix $P^{(3)}$

A_i	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8	F_9	F_{10}
A_1	VI	I	VU	I	I	I	VI	I	VI	VI
A_2	VI	VI	VI	I	VI	I	I	VI	VI	VI
A_3	I	VI	VI	VI	VI	VI	I	I	I	I
A_4	VI	I	I	VU	I	VI	VU	I	I	VI

Table 6: Decision matrix $P^{(4)}$

A_i	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8	F_9	F_{10}
A_1	VI	VI	VI	VI	I	VI	VI	I	EI	EI
A_2	I	I	VI	EI	VI	I	I	VI	VI	VI
A_3	VI	VI	I	I	I	I	VI	EI	I	I
A_4	I	VI	VI	I	EI	VI	I	I	EI	I

Table 7: Decision matrix $P^{(5)}$

A_i	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8	F_9	F_{10}
A_1	VI	I	VI	VU	VI	VI	I	EI	I	VI
A_2	I	VI	VU	I	VI	VU	VU	I	VI	I
A_3	I	I	I	I	I	I	I	I	I	I
A_4	VI	VI	VI	VI	VI	VI	VI	VI	VU	VU

Step 1: Construction of the decision matrices

$$\begin{matrix} A_1 \\ A_2 \\ A_3 \\ A_4 \end{matrix}\begin{pmatrix} \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.90,0.10,0.10\rangle & \langle 0.90,0.10,0.10\rangle \\ \langle 0.90,0.10,0.10\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.90,0.10,0.10\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.90,0.10,0.10\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.35,0.60,0.70\rangle \\ \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.35,0.60,0.70\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.35,0.60,0.70\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle \\ \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.35,0.60,0.70\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle \end{pmatrix}$$

$$\begin{matrix} A_1 \\ A_2 \\ A_3 \\ A_4 \end{matrix}\begin{pmatrix} \langle 0.80,0.20,0.15\rangle & \langle 0.35,0.60,0.70\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.90,0.10,0.10\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.90,0.10,0.10\rangle & \langle 0.80,0.20,0.15\rangle \\ \langle 0.80,0.20,0.15\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.35,0.60,0.70\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle \\ \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.35,0.60,0.70\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.80,0.20,0.15\rangle \\ \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.35,0.60,0.70\rangle & \langle 0.35,0.60,0.70\rangle & \langle 0.35,0.60,0.70\rangle & \langle 0.35,0.60,0.70\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.35,0.60,0.70\rangle & \langle 0.50,0.40,0.45\rangle \end{pmatrix}$$

$$\begin{matrix} A_1 \\ A_2 \\ A_3 \\ A_4 \end{matrix}\begin{pmatrix} \langle 0.80,0.20,0.15\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.35,0.60,0.70\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle \\ \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle \\ \langle 0.50,0.40,0.45\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle \\ \langle 0.80,0.20,0.15\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.35,0.60,0.70\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.35,0.60,0.70\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.80,0.20,0.15\rangle \end{pmatrix}$$

$$\begin{matrix} A_1 \\ A_2 \\ A_3 \\ A_4 \end{matrix}\begin{pmatrix} \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.90,0.10,0.10\rangle & \langle 0.90,0.10,0.10\rangle \\ \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.90,0.10,0.10\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle \\ \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.90,0.10,0.10\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle \\ \langle 0.50,0.40,0.45\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.90,0.10,0.10\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.90,0.10,0.10\rangle & \langle 0.50,0.40,0.45\rangle \end{pmatrix}$$

$$\begin{matrix} A_1 \\ A_2 \\ A_3 \\ A_4 \end{matrix}\begin{pmatrix} \langle 0.80,0.20,0.15\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.35,0.60,0.70\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.90,0.10,0.10\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.80,0.20,0.15\rangle \\ \langle 0.50,0.40,0.45\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.35,0.60,0.70\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.35,0.60,0.70\rangle & \langle 0.35,0.60,0.70\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.50,0.40,0.45\rangle \\ \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle & \langle 0.50,0.40,0.45\rangle \\ \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.80,0.20,0.15\rangle & \langle 0.35,0.60,0.70\rangle & \langle 0.35,0.60,0.70\rangle \end{pmatrix}$$

Step 2: Normalisation of the matrices

All the criteria are benefit type. So, no need to normalise them.

Step 3: Calculate the weights of the DMs

According to the equation (13) we obtain the weights of the decision makers (see table 8):

Table 8: Weight of the decision makers

Decision Maker	φ_1	φ_2	φ_3	φ_4	φ_5
Weight	0.2078	0.1882	0.1882	0.2078	0.2078

Step 4: Construction of the aggregated decision matrix

By using Eq. (10), the aggregated value of the five decision makers' assessment values is arbitrarily chosen as an illustration for the alternative A1 with respect to the attribute F1 and shown in Eqs. (15), (16), and (17).

$$T_{11}=1-(1-0.80)^{0.2078}\times(1-0.80)^{0.1882}\times(1-0.80)^{0.1882}\times(1-0.80)^{0.2078}\times(1-0.80)^{0.2078}$$

$$=0.8 \qquad (15)$$

$$I_{11}=(0.20)^{0.2078}\times(0.20)^{0.1882}\times(0.20)^{0.188}2\times(0.20)^{0.2078}\times(0.20)^{0.2078}$$

$$=0.2 \qquad (16)$$

$$F_{11}=(0.15)^{0.2078}\times(0.15)^{0.1882}\times(0.15)^{0.1882}\times(0.15)^{0.2078}\times(0.15)^{0.2078}$$

$$=0.15 \qquad (17)$$

$$\begin{matrix} A_1 \\ A_2 \\ A_3 \\ A_4 \end{matrix}\begin{pmatrix} \langle 0.80,0.20,0.15\rangle & \langle 0.64,0.32,0.31\rangle & \langle 0.7,0.28,0.25\rangle & \langle 0.64,0.33,0.31\rangle & \langle 0.66,0.3,0.29\rangle & \langle 0.72,0.26,0.23\rangle & \langle 0.79,0.2,0.17\rangle & \langle 0.7,0.26,0.26\rangle & \langle 0.84,0.15,0.15\rangle & \langle 0.85,0.15,0.13\rangle \\ \langle 0.75,0.23,0.22\rangle & \langle 0.71,0.26,0.25\rangle & \langle 0.61,0.36,0.35\rangle & \langle 0.74,0.23,0.24\rangle & \langle 0.8,0.2,0.15\rangle & \langle 0.63,0.33,0.32\rangle & \langle 0.63,0.33,0.32\rangle & \langle 0.75,0.23,0.21\rangle & \langle 0.76,0.23,0.19\rangle & \langle 0.69,0.29,0.26\rangle \\ \langle 0.66,0.3,0.29\rangle & \langle 0.71,0.26,0.25\rangle & \langle 0.65,0.31,0.29\rangle & \langle 0.63,0.34,0.33\rangle & \langle 0.71,0.27,0.24\rangle & \langle 0.56,0.38,0.4\rangle & \langle 0.59,0.35,0.36\rangle & \langle 0.62,0.32,0.36\rangle & \langle 0.5,0.4,0.45\rangle & \langle 0.58,0.35,0.37\rangle \\ \langle 0.76,0.23,0.19\rangle & \langle 0.76,0.23,0.18\rangle & \langle 0.76,0.23,0.18\rangle & \langle 0.62,0.35,0.34\rangle & \langle 0.74,0.24,0.23\rangle & \langle 0.75,0.25,0.2\rangle & \langle 0.52,0.44,0.46\rangle & \langle 0.65,0.3,0.29\rangle & \langle 0.6,0.35,0.39\rangle & \langle 0.56,0.38,0.4\rangle \end{pmatrix}$$

Step 5: Calculate the weights of the attributes

To determine the weights of 10 attributes, we calculate the entropy value of each attribute using the formula (13) . The entropy values are presented in table 9.

Table 9: Entropy value for attributes

E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8	E_9	E_{10}
0.8013	0.8248	0.8448	0.8553	0.8109	0.8516	0.8698	0.8292	0.8307	0.8400

After calculating the entropy values of all ten attributes, we calculate the weight of each attribute using the formula (14) (see table 10).

Table 10: Attribute weight calculated according to entropy strategy (1st Case)

ω	W_1	W_2	W_3	W_4	W_5	W_6	W_7	W_8	W_9	W_{10}
Value	0.1210	0.1067	0.0945	0.0882	0.1152	0.0904	0.0793	0.1040	0.1031	0.0975
Position	1st	3rd	7th	9th	2nd	8th	10th	4th	5th	6th

In table 11, the sensitivity analysis is shown between the weights of the DMs, weights of the RFs and their ranking.

Table 11: Assigning of DMs'weight and corresponding weight of RFs and their ranking.

Weights of DMs / Weights of RFs			W	ei	W3	W4	W5	W6	W7	W8	W9	W10
1st Case	DM1	0.2078	0.1210	0.1067	0.0945	0.0882	0.1152	0.0904	0.0793	0.1040	0.1031	0.0975
	DM2	0.1882										
	DM3	0.1882										
	DM4	0.2078										
	DM5	0.2078										
	Ranking order of RFs		1st	3rd	7th	9th	2nd	8th	10th	4th	5th	6th
2nd Case	DM1	0.2	0.1207	0.1063	0.0954	0.0890	0.1152	0.0905	0.0793	0.1037	0.1023	0.0976
	DM2	0.2										
	DM3	0.2										
	DM4	0.2										
	DM5	0.2										
	Ranking order of RFs		1st	3rd	7th	9th	2nd	8th	10th	4th	5th	6th
3rd Case	DM1	0.1	0.1288	0.1007	0.0923	0.0781	0.1088	0.0924	0.0849	0.0905	0.1042	0.1192
	DM2	0.35										
	DM3	0.35										
	DM4	0.1										
	DM5	0.1										
	Ranking order of RFs		1st	5th	7th	10th	3rd	6th	9th	8th	4th	2nd
4th Case	DM1	0.185										
	DM2	0.2225										
	DM3	0.2225	0.1209	0.1046	0.0954	0.0887	0.1144	0.0905	0.0798	0.1040	0.1021	0.0996
	DM4	0.185										
	DM5	0.185										
	Ranking order of RFs		1st	3rd	7th	9th	2nd	8th	10th	4th	5th	6th
5th Case	DM1	0.3	0.1186	0.114	0.1033	0.0968	0.1071	0.0908	0.0645	0.1178	0.1048	0.0823
	DM2	0.05										
	DM3	0.05										
	DM4	0.3										
	DM5	0.3										
	Ranking order of RFs		1st	3rd	6th	7th	4th	8th	10th	2nd	5th	9th
6th Case	DM1	0.25	0.1220	0.1123	0.1008	0.0964	0.1072	0.0913	0.0623	0.1108	0.1057	0.0913
	DM2	0.125										
	DM3	0.125										
	DM4	0.25										
	DM5	0.25										
	Ranking order of RFs		1st	2nd	6th	7th	4th	8th	10th	3rd	5th	9th

Step 6: Arrange the attributes in descending order

Now finally we obtain the weights of the factors and are arranged considering the weight (ω_s) in descending order we get

$F_1 > F_5 > F_2 > F_8 > F_9 > F_{10} > F_3 > F_6 > F_4 > F_7$.

7.1 Sensitivity analysis

If the weights of the DMs have been changed, then it impacts (See Fig. 2 and Table 11) the ranking of RFs. If equal weights are considered for the DMs (2nd Case), then we see that the ranking order of the RFs remains unchanged. However, when (3rd Case) the 2nd and 3rd DMs are considered greater weights (0.35,0.35) than less weights for the 1st, 4th and 5th DMs (0.1, 0.1, 0.1), we see that ranking order is changed but the 1st position remains unchanged. The same trend of results has been observed in 4th case also. On the other hand (5th and 6th Case), when the 1st , 4th and 5th DMs' weights are considered greater (0.3, 0.3, 0.3) than other two DMs (0.05, 0.05), the order of the RFs' changed but the 1st position remains unchanged.

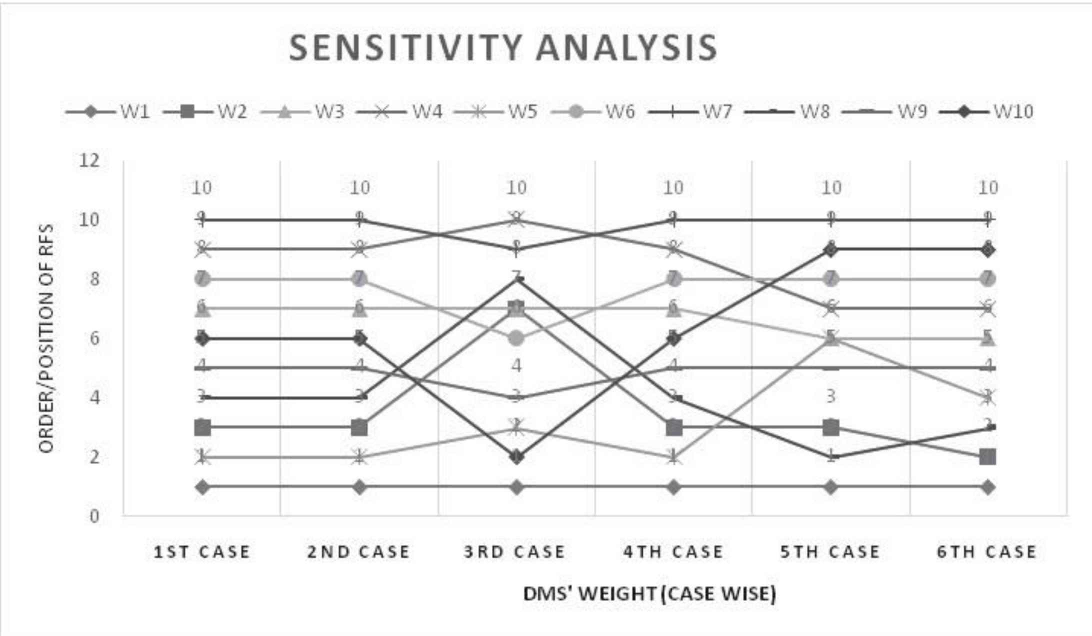

Fig. 2 : Sensitivity analysis of the decision makers' weights

Strength of the study: The proposed framework is capable of dealing with neutrosophic information. It has a tremendous capacity to incorporate numerous ranking factors from different stakeholders of IR like document, information seekers, tools, and social networks etc.

8. Conclusion

This paper develops the SVNN-Entropy Weighting Strategy using the SVNNWAA operator in SVNN settings. The paper presents the ranking factors under group popularity and assigns weight to each individual ranking factor based on assessments of experts cum users using the entropy strategy. Here, we have proposed a framework to incorporate the factors after assigning weights. SVNN-EWS is the first approach in the field of information retrieval to consider SVNN environment with modern practices.

8.1 Limitations

For a large number of data, manual system will not perform well. The ranking factors are not easily understandable by the respondents.

8.2 Future scope of the study

Artificial Intelligence (AI) can be employed to collect and manage all the aspects of the proposed framework. More RFs can be incorporated for exhaustive model. It is also helpful when designing a ranking model for a library and information system (LIS), designing discovery tools, or discussing with an ILMS vendor.

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