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A decision making model for selecting start-up businesses in a government venture capital scheme

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Abstract

Purpose – The purpose of this paper is to propose an intuitionistic fuzzy technique for order preference by similarity to ideal solution (TOPSIS) multi-criteria decision making method for the selection of start-up businesses in a government venture capital (GVC) scheme. Most GVC funded start-ups fail or underperform compared to those funded by private VCs due to a number of reasons including lack of transparency and unfairness in the selection process. By its design, the proposed method is able to increase transparency and reduce the influence of bias in GVC start-up selection processes. The proposed method also models uncertainty in the selection criteria using fuzzy set theory that mirrors the natural human decision-making process.

Design/methodology/approach – The proposed method first presents a set of criteria relevant to the selection of early stage but high-potential start-ups in a GVC financing scheme. These criteria are then analyzed using the TOPSIS method in an intuitionistic fuzzy environment. The intuitionistic fuzzy weighted averaging Operator is used to aggregate ratings of decision makers. A numerical example of how the proposed method could be used in GVC start-up candidate selection in a highly competitive GVC scheme is provided.

Findings – The methodology adopted increases fairness and transparency in the selection of start-up businesses for fund support in a government-run VC scheme. The criteria set proposed is ideal for selecting start-up businesses in a government controlled VC scheme. The decision-making framework demonstrates how uncertainty in the selection criteria are efficiently modelled with the TOPSIS method.

Practical implications – As GVC schemes increase around the world, and concerns about failure and underperformance of GVC funded start-ups increase, the proposed method could help bring formalism and ensure the selection of start-ups with high potential for success.

Originality/value – The framework designs relevant sets of criteria for a selection problem, demonstrates the use of extended TOPSIS method in intuitionistic fuzzy sets and apply the proposed method in an area that has not been considered before. Additionally, it demonstrates how intuitionistic fuzzy TOPSIS could be carried out in a real decision-making application setting.

Keywords Decision making, Start-up businesses, Government venture capital (GVC), Intuitionistic fuzzy TOPSIS (IFS)

Paper type Research paper

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1. Introduction

Venture capital (VC) investment is proving to be the mainstay in the lives of start-up businesses around the world, especially those in the “high-tech” industry. Evidence from the USA, Europe, China, India, Canada and Israel, points to a gradual global acceptance of VC support for early stage but high-potential businesses. In 2013, global VC investment was estimated at US$48.5 billion (Ernst & Young, 2014). According to Bertoni et al. (2011), Gompers and Lerner (2004), Chemmanur et al. (2011) and Alperovych et al. (2015), there is enough evidence to show that the commercial success rates of start-up businesses that receive support from VC far outweigh those that do not receive any such supports. However, in recent times, due to very strict demands on start-up businesses from Private Venture Capitalists (PVCs) and the apparent lack of opportunities at securing financial support through traditional investment sources, many governments around the world have joined the fray as far as VC investment is concerned (Bertoni and Tykvová, 2015; Nkusu, 2011; Colombo et al., 2014). For instance, in Europe, a total of 40 per cent of all VC investments in 2013 were reported to have come from their governments. Similarly in the USA, the federal government’s Small Business Innovation Research programme is the single largest investor of early stage innovations (Ernst & Young, 2014; Audretsch, 2003; Lerner, 2000). Government venture capital (GVC) is also quite popular in Brazil, Russia, India, China and South Africa and in developing countries where private VC funding are hard to come by compared to what exist in the USA and Europe (Ernst & Young, 2014). In spite of the growing interests in GVCs, many studies report of a worrying trend of GVC supported early stage businesses underperforming against their counterparts that obtain funding from PVCs (Brander et al., 2008; Luukkonen et al., 2013; Grilli and Murtinu, 2014; Alperovych et al., 2015; Bertoni and Tykvová, 2012). A number of reasons for the underperformance has been offered. Some authors assert that the selection process in GVC schemes lack the rigorousness demanded in PVC schemes (Christofidis and Debane, 2001; Leleux and Surlemont, 2003). Many also cite the undue influence of political and pressure groups (usually aligned with governments) as a major reason for the poor performance of GVC funded start-up businesses (Knoesen, 2009; Nattrass and Seekings, 2001; Iheduru, 2004). Others also argue that such underperformance is exacerbated by the lack of models that explicitly feature important aspects of the selection process such as uncertainties in some of the evaluation criteria (Zacharakis and Shepherd, 2001; Muzyka et al., 1996; Zacharakis and Meyer, 2000). This paper addresses the concerns of such authors and proposes a model for the evaluation and selection of start-up businesses in a GVC scheme that incorporates uncertainties in the selection criteria. To do this, the paper first contrasts GVCs with PVCs for a better understanding of their differences and subsequently, the reasons why GVC funded start-ups usually underperform against PVC funded start-ups.

1.1 PVCs vs GVCs

The main objective of a PVC firm is to generate enough returns for its investors and maximize their value typically above the level of the public equity markets (Mulcahy, 2014). The fear of losing investors, guide PVC firms to avoid favouritism in the selection of start-up businesses. In view of this, a candidate start-up technology business must have high potential to succeed and demonstrate the ability to make significant profits over a period of time. With this in mind, PVCs usually look out for early entrepreneurs that can deliver impressive growth within specific time period, typically not more than six years (Da Rin et al., 2011).
To reduce the chances of failure, PVC funded start-up businesses typically undergo lengthy and demanding screening processes (Landström, 2007; Lerner, 2002). PVCs also place greater emphasis on the experience of the management team and often demand a representation on the management board of the start-up firm so as to be able to monitor and prevent wasteful spending that may derail the development and growth of the business (Chemmanur et al., 2011; Lerner, 2002). PVCs are prevalent in the information systems sector, and also in some specific health sectors such as the pharmaceutical industry (Lerner, 2002).

GVCs on the other hand, mostly operate in sectors that normally lack VC financing such as education, environment and health sectors (Lerner, 2002). They usually fund start-ups that possess promising technology beneficial to society but which lack the necessary funding to bring the technology to fruition. In this regard, technologies with potential to spawn positive externalities, such as those with prospects of stimulating growth in other sectors, have higher chances of attaining GVC funding (Lerner, 2002). Since the main objective of a GVC investment is welfare maximization to the state, GVCs demand rates of returns tend to be far lower than that of a typical PVC (Griliches, 1992). As a result, a GVC investment might not yield direct monetary profit to the state and could still be considered a success. GVC investments are usually subject to statutory terms and conditions in respect to the type of investments and the manner at which the investment is carried out (Landström, 2007). Most often however, such terms and conditions are less stricter than those of PVCs.

Using data from the VC industry in Belgium, Alperovych et al. (2015) finds that PVC-backed firms are more efficient than GVC-backed firms. More tellingly, they find that GVC-backed firms are less efficient than non-VC-backed firms. PVC-backed companies also mostly meet exiting deadlines and conditionalities than GVC-backed companies (Cumming et al., 2014; Chemmanur et al., 2011; Luukkanen et al., 2013; Bertoni and Tykvová, 2012; Brander et al., 2008). Grilli and Murtini (2014) show in their study that PVC funding leads to increase growth in new start-ups than GVC funding. Lerner (2002) also finds that a prevalent characteristics among underachieving start-up companies is that most are funded through research grants from government agencies.

A number of factors could account for the gap in performance. Some of these are low capital recovery rates and undefined exit paths for candidate start-up businesses in GVC schemes (Biekpe, 2004). In addition, unlike PVCs, GVCs usually do not require a position on the management team of the start-up company. The lack of involvement by GVCs in the management team (and therefore lack of proper monitoring) of the start-up company is believed by many as one of the main reasons why GVC funded start-ups underperform compared to PVC funded start-ups (Chemmanur et al., 2011; Cumming, 2007). Without proper monitoring, it is easy for a start-up firm to engage in over spending or lose focus and venture into business programmes unrelated to the original business idea. Furthermore, Christofidis and Debande (2001) observed that most GVCs are run by inexperienced civil servants who are less motivated unlike their counterpart fund managers at PVCs. Leleux and Surlemont (2003); Meyer and Mathonet (2011) explain that the seeming lack of motivation of government staff at GVCs, is because they do not directly share in returns that accrue to the GVCs they manage. There are also the criticisms of an apparent lack of robust selection criteria (Bertoni et al., 2011), lack of due diligence in the selection process (Baeyens et al., 2006), poor programme design and implementation challenges (Lerner, 2009) in GVCs. The award of GVC funds to start-ups, unlike in PVCs, is prone to biases and
favouritism (which consequently could lead to failure) since selection could be influenced by powerful interest groups aligned to governments and politicians who may seek to direct the award of GVC funding in a manner that benefits themselves (Cumming, 2007; Lerner, 2002) and their constituents. This is especially the case in developing countries where selection of candidates for such capital financing schemes are sometimes clouded by political, tribal and social affiliations (Nkusu, 2011). According to Pina-Stranger and Lazega (2011) and Sorenson and Rogan (2014), these challenges could be avoided or their impact mitigated through a transparent decision making process (devoid of personal ties and affiliations) for selecting start-up businesses.

These observations have led to a renewed interests in research aimed at improving the performance of GVCs (Munari and Toschi, 2015). One of such interest is a mechanism for a transparent and efficient decision making process for determining the commercial viability and the eventual selection of a technology start-up business in a government-run VC.

Any such decision-making mechanism must be able to address the problems listed above including that of bias and favouritism. More importantly, the mechanism must place greater importance on the need for effective management team for the success of the start-up.

1.2 Research gap
Some non-fuzzy decision-making models for evaluating and selecting start-ups in VC financing schemes have been proposed. Woike et al. (2015) used computer simulation to study the impact of different strategies on the financial performance of VCs. Riquelme and Rickards (1992) proposed a self-explicated, hybrid conjoint model to aid the selection of start-ups for financing in a VC scheme. These non-fuzzy methods rely on historical data of past beneficiaries to arrive at a decision. This approach may not all the time be appropriate for assessing and selecting early stage entrepreneurs that have little or no past data and might lead to sub-optimal decisions. Since future values of data needed for evaluation are uncertain at the time of selection, fuzzy models that have the ability to explicitly consider uncertainty in the models might be appropriate.

The main objective of this paper is therefore to propose a fuzzy multi-criteria decision making (MCDM) model for the selection of start-ups in GVCs that addresses the obvious uncertainty problems in such decision problems. It is also hoped that the proposed approach would help generate interest regarding research in decision models for VC selection problems.

In our search of literature, only the works of Zhang (2012), and Aouni et al. (2014), attempt to use fuzzy theory for selecting start-up businesses in a VC. Aouni et al. (2014) used a fuzzy goal programming approach to model uncertainty. However, such models cannot accommodate qualitative factors such as leadership experience and product quality. Zhang (2012), considers fuzziness but only in the weights of the evaluators and not in the values for the competing start-up candidates. Zhang (2012) also does not explicitly model uncertainty but instead attempts to overcome it using entropy technique to determine the weights. The model by Zhang (2012) is a combination of an optimization and a multi-attribute model that seeks to select a candidate based on maximizing risk-adjusted returns. In contrast, our proposed approach uses a multi-attribute model to generate a composite index that however takes qualitative factors as well as a “more is better” and a “less is better” criterion into account. By considering uncertainties directly in the values for assessment, the proposed intuitionistic fuzzy technique for order preference by similarity to ideal solution (TOPSIS) framework is thus more efficient at modelling the natural thought processes of
humans in decision making. The proposed decision framework also includes selection criteria specially tailored to address challenges faced by GVCs such as bias and favouritism, as well as ascertaining the effectiveness of the management team of the start-ups. The proposed method in particular can be used to help address some of the challenges encountered in the selection of start-up businesses especially in a government high priority area such as in information systems/information communication technology (IS/IT) sectors. This is because selecting the ideal start-up to support in IS/IT areas can be very challenging and complex since most of the criteria involved are subjective or hold uncertain data (Pina-Stranger and Lazega, 2011).

The rest of the paper is organized as follows. First, an elaborate selection criteria that hinge on the attainment of the objectives of a GVC and the success of the start-up business culled from literature is introduced. This is followed by a methodology comprising of an introduction to classical fuzzy set theory and its extension into intuitionistic fuzzy sets (IFS), especially as used in decision making. Next is a systematic outline with definitions and formulas of intuitionistic fuzzy TOPSIS method to help select potential candidates in a highly competitive but limited funding situation in a GVC programme. Finally, a numerical example of how intuitionistic fuzzy TOPSIS could be used to rank and select high-potential start-ups in a government backed VC is illustrated.

2. GVC funded start-up business selection criteria
Several authors have researched into the main criteria used by venture capitalists to evaluate start-up businesses. Table I summarizes major works on these criteria in the literature, particularly those relevant to GVC schemes. The criteria under entrepreneur/team personality, entrepreneur/team experience, and product or service potential, model qualitative attributes whiles the criteria under financial characteristics, market characteristics and social impact/contribution model quantitative criteria. As can be perceived from the criteria, the relevant values needed for evaluation cannot be determined in the present time but must be estimated based on the judgement of experts. In classical decision analysis, possible outcomes with their probabilities of occurrence would be considered in the final decision making. In the case where qualitative criteria are present, such uncertainty can be modelled using fuzzy theory that is able to accommodate both qualitative and quantitative criteria. The next section gives brief introduction to fuzzy theory and its extension to intuitionistic fuzzy TOPSIS.

3. Methodology
3.1 Modelling subjectivity with IFS
According to Hisrich and Jankowicz (1990) and Mitchell et al. (2005), venture capitalists use many subjective criteria and intuition in their decision making. In view of this, research must focus on developing methods that model the intuition and the subjectiveness in the selection process. This section introduces the fuzzy concept that is generally used to model intuition and subjectivity in human decision making processes such as that of start-up business selection. The notion of fuzzy set theory was proposed by Zadeh (1965) as a mathematical construct to help deal with issues of uncertainty, subjectivities, vagueness and imprecision in human judgments (Afful-Dadzie et al., 2014). Since the conception of fuzzy set theory, it has successfully been applied in many areas including situations that demand efficient modelling of human decisions and judgments (Wang, 1999; Klir and Yuan, 1995). In addition, several extensions and
modifications of the original fuzzy concept have been proposed to address different instances of uncertainty with regard to a decision maker’s judgment. One of such extensions is Atanasov’s IFS proposed in 1986 to improve the modelling of uncertain information (Atanassov, 1986). For instance in a competitive start-up businesses selection programme, IFS helps decipher how decision makers make their judgments

<table>
<thead>
<tr>
<th>Major decision criteria</th>
<th>Sub-criteria</th>
<th>Literature support of criterion importance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Entrepreneur/team personality</td>
<td></td>
<td></td>
</tr>
<tr>
<td>C1: Leadership experience</td>
<td>MacMillan et al. (1985), Zacharakis and Shepherd (2001)</td>
<td></td>
</tr>
<tr>
<td>C2: Vision</td>
<td>MacMillan et al. (1985)</td>
<td></td>
</tr>
<tr>
<td>C6: Team understanding/</td>
<td>Mason and Stark (2004), Mason and Harrison (2002)</td>
<td></td>
</tr>
<tr>
<td>co-operation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>C7: Track record</td>
<td>Haines et al. (2003), Flynn (1991)</td>
<td></td>
</tr>
<tr>
<td>C9: Business qualification</td>
<td>Shepherd (1999a, b), Franke et al. (2006)</td>
<td></td>
</tr>
<tr>
<td>understanding</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Product or Service Potential</td>
<td></td>
<td></td>
</tr>
<tr>
<td>C12: Patentability</td>
<td>Tyebjee and Bruno (1984), MacMillan et al. (1985)</td>
<td></td>
</tr>
<tr>
<td>Financial characteristics</td>
<td></td>
<td></td>
</tr>
<tr>
<td>C15: Level of riskiness</td>
<td>Haines et al. (2003), Nkusu, (2011)</td>
<td></td>
</tr>
<tr>
<td>C16: Cost of investment</td>
<td>Haines et al. (2003), Feeney et al. (1999)</td>
<td></td>
</tr>
<tr>
<td>C17: Capital recovery</td>
<td>Muzyka et al. (1996), Mason and Stark (2004)</td>
<td></td>
</tr>
<tr>
<td>C18: Exit strategy</td>
<td>Feeney et al. (1999), Fried and Hisrich (1994)</td>
<td></td>
</tr>
<tr>
<td>Market characteristics</td>
<td></td>
<td></td>
</tr>
<tr>
<td>C23: Competitive strength/</td>
<td>Alperovych et al. (2015), Bachher and Guild (1996)</td>
<td></td>
</tr>
<tr>
<td>advantage</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Societal impact/contribution</td>
<td></td>
<td></td>
</tr>
<tr>
<td>C25: Economic impact on the region</td>
<td>Haines et al. (2003), Van Osnabrugge and Robinson (2000)</td>
<td></td>
</tr>
<tr>
<td>C26: Potential growth into an industry</td>
<td>Feeney et al. (1999), Haines et al. (2003)</td>
<td></td>
</tr>
</tbody>
</table>

Table I. Criteria for selecting start-up businesses in a government-run venture capital
In IFS, a set where \( \mu \) Power of an intuitionistic fuzzy set: expressed as \( A \) by revealing how much of approval, disapproval and doubt in each decision maker’s rating. Generally, IFS differs from classical fuzzy sets in terms of the approach in that, IFS introduces three functions that express the degree of membership, non-membership and hesitancy (Chen, 2014). Intuitively, the IFS approach gives a different dimension to human decision modelling by introducing three states of fuzzy constructs to characterize the extent to which decision-makers support, oppose and are hesitant or neutral about their decisions (Li, 2014). In other words, the IFS approach helps to quantify the extent of satisfaction, dissatisfaction and hesitancy in a decision maker’s judgment. In the following, basic definitions of fuzzy set and IFS are presented:

Definition 1. Fuzzy sets.

In classical fuzzy set, a fuzzy set \( A \) in \( X \) is characterized by membership functions expressed as \( A = \{(x, \mu_A(x))|x \in X\} \) where \( \mu_A: X \to [0, 1] \) describes the membership function of the fuzzy set \( A \) within the interval of \([0, 1]\).

Definition 2. IFS.

In IFS, a set \( A \) in \( X \) is defined as \( A = \{(x, \mu_A(x), v_A(x))|x \in X\} \) where \( \mu_A(x), v_A(x): X \to [0, 1] \), respectively represent membership and non-membership functions on condition that \( 0 \leq \mu_A(x) + v_A(x) \leq 1 \). Additionally, IFS introduces a third construct \( \pi_A(x) \), the intuitionistic index which expresses whether or not \( x \) belongs to \( A \):

\[
\pi_A = 1 - \mu_A(x) - v_A(x)
\] (1)

The intuitionistic index in Equation 1 measures the hesitancy degree of element \( x \) in \( A \) where it becomes obvious that \( 0 \leq \pi_A(x) \leq 1 \) for each \( x \in X \). A small value of \( \pi_A(x) \) implies that information about \( x \) is more certain (Boran et al., 2009). On the other hand, a higher value of the hesitancy degree \( \pi_A(x) \) means the information that \( x \) holds is more uncertain. An intuitionistic fuzzy set can therefore fully be defined as:

\[
A = \{(x, \mu_A(x), v_A(x), \pi_A(x))|x \in X\}
\] (2)

where \( \mu_A \in [0, 1]; v_A \in [0, 1]; \pi_A \in [0, 1] \).

In summary, the three constructs \((x, \mu_A(x), v_A(x), \pi_A(x))\) basically reveal the extent of satisfaction, dissatisfaction and hesitancy in a decision maker’s assessment of an alternative or criteria.

Definition 3. Basic arithmetic operations of IFS.

Let \( A = \{(x, \mu_A(x), v_A(x))|x \in X\} \) and \( B = \{(x, \mu_B(x), v_B(x))|x \in X\} \) be two intuitionistic fuzzy numbers (IFNs). Some basic operations on these IFNs \( A \) and \( B \) applied in this paper are expressed as follows:

\[
A \oplus B = \{(x\mu_A(x) + \mu_B(x) - \mu_A(x) \cdot \mu_B(x), v_A(x) \cdot v_B(x))|x \in X\}
\] (3)

\[
A \otimes B = \{(x\mu_A(x) \cdot \mu_B(x), v_A(x) + v_B(x) - v_A(x) \cdot v_B(x))|x \in X\}
\] (4)

Product of an intuitionistic fuzzy set and a real number is defined as follows:

\[
\lambda A = \left\{ \left( 1 - (1 - \mu_A(x))^\lambda, (v_A(x))^{1/\lambda} \right) | x \in X \right\}
\] (5)

Power of an intuitionistic fuzzy set:

\[
A^\lambda = \left\{ \left( (\mu_A(x))^\lambda, 1 - (1 - v_A(x))^\lambda \right) | x \in X \right\}
\] (6)
3.2 Intuitionistic fuzzy TOPSIS

The TOPSIS method was proposed by Hwang and Yoon (1981) and has since become one of the popular techniques in MCDM. Like the original TOPSIS method, fuzzy TOPSIS also relies on the so-called shortest distance from the fuzzy positive ideal solution (FPIS) and the farthest distance from the fuzzy negative ideal solution (FNIS) to determine the best alternative. The FNIS maximizes the cost criteria and minimizes the benefit criteria, whereas FPIS maximizes benefit criteria and minimizes cost criteria. The alternatives are ranked and selected according to their relative closeness determined using the two distance measures. Similarly, the extension of TOPSIS into IFS also maintains the key features such as the FPIS and the FNIS (Boran et al., 2009). In the following, we outline the proposed method that incorporates IFS into fuzzy TOPSIS.

3.3 Steps for Intuitionistic fuzzy TOPSIS

Step 1. Determining sets of alternatives, criteria, linguistic variables and decision-makers.

As it is usual with MCDM methods, the alternatives to be ranked, the criteria to be used in the ratings and the group of decision-makers are determined. In view of this, let $A = \{A_1, A_2, ..., A_m\}$ be the set of alternatives to be considered, $C = \{C_1, C_2, ..., C_n\}$, the set of criteria and, $k = \{D_1, D_2, ..., D_d\}$ the sets of decision makers. Equation (7), shows a decision matrix for decision maker, $k = 1, 2, ..., d$:

$$
\tilde{k} = \begin{bmatrix}
\tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\
\tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
\tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn}
\end{bmatrix}, \quad i = 1, 2, \ldots, m; \quad j = 1, 2, \ldots, n \quad (7)
$$

where $\tilde{x}_{ij}$ is the rating of alternative $A_i$ with respect to criterion $C_j$ both expressed in IFS. This implies that the rating of a decision maker $k$ is expressed as $\tilde{x}_{ij}^k = \langle \tilde{u}_{ij}^k, \tilde{v}_{ij}^k, \tilde{p}_{ij}^k \rangle$. Additionally, the linguistic variables (criteria) to be used in the assessment of start-up candidates are determined. The linguistic variables are further expressed in linguistic terms and used to rate the performance of each alternative with respect to a linguistic variable (Kuo and Liang, 2012). In this paper, the format of the linguistic terms are expressed in IFNs as seen in Table II. Linguistic terms are qualitative words that describe the subjective view of a decision maker about a criterion with respect to each alternative (Klir and Yuan, 1995). In Table II the linguistic terms and their IFNs are presented.

<table>
<thead>
<tr>
<th>Linguistic terms</th>
<th>IFS fuzzy number</th>
<th>Ratings of alternatives</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very low (VL)</td>
<td>(0.05, 0.95)</td>
<td>Not acceptable (NA)</td>
</tr>
<tr>
<td>Low (L)</td>
<td>(0.2, 0.75)</td>
<td>Slightly acceptable (SA)</td>
</tr>
<tr>
<td>Medium (M)</td>
<td>(0.55, 0.4)</td>
<td>Acceptable (A)</td>
</tr>
<tr>
<td>High (H)</td>
<td>(0.75, 0.2)</td>
<td>Highly acceptable (HA)</td>
</tr>
<tr>
<td>Very high (VH)</td>
<td>(0.95, 0.05)</td>
<td>Very highly acceptable (VHA)</td>
</tr>
</tbody>
</table>

Table II. Linguistic scale for the importance of criterion and alternative ratings
Step 2. Determining importance weights of decision-makers. In this step, the weights of the decision makers are determined by weighting their relative importance towards the final decision to be made. This is premised on the assumption that not all decision makers are equal in importance and that there is a higher decision authority that rates to assign weight to the decision makers. This rating is linguistically expressed in IFN format. Let $\tilde{D}_k = \{\tilde{u}_k, \tilde{v}_k, \tilde{\pi}_k\}$ be an IFN expressing the rating of a $k$th decision maker.

Then the importance weight of the $k$th decision maker may be expressed below (Boran et al., 2009):

$$\tilde{r}_k = \frac{\tilde{u}_k + \tilde{\pi}_k}{\sum_{k=1}^{d} (\tilde{u}_k + \tilde{\pi}_k)}$$

Step 3. Determining weights of each criterion. In this step, decision makers rate to determine the importance or the weight of each criterion with the help of the linguistic terms in Table I. In the following, $w_j$ denotes the weight of the criterion $C_j$ based on the linguistic preference assigned by a decision maker. It is noted that the weight $\tilde{W} = [\tilde{w}_1, \tilde{w}_2, \ldots, \tilde{w}_n]$ is expressed as an intuitionistic fuzzy set $\tilde{w}_j = (\tilde{\mu}_j, \tilde{\nu}_j, \pi_j)$ where as usual $\pi_j = 1 - \mu_j(x) - \nu_j(x)$.

Step 4. Aggregation of decisions. In step 4, the ratings of the decision makers concerning the alternatives and criteria importance which are expressed in IFS are aggregated. Let $\tilde{S}_k = (\tilde{x}_{ij}^k)_{m \times n}$ express the intuitionistic fuzzy matrix of each of the decision makers and $\tilde{\rho} = \{\tilde{\rho}_1, \tilde{\rho}_2, \ldots, \tilde{\rho}_d\}$, the importance weight of each decision maker where $\sum_{k=1}^{d} \rho_k = 1$, $\rho_k \in [0, 1]$.

The importance of aggregation in group decision making processes cannot be overemphasized. Aggregation operators are used to sum up all individual ratings into a composite decision for the group of decision makers. In fuzzy decision modelling, many aggregation operators have been proposed with the majority belonging to the families of averaging operators, ordered weight aggregation, compensatory operators, geometric operators, Shapley averaging operators, Sugeno integrals, Choquet operators and many other hybrid forms. In this paper, the intuitionistic fuzzy weighted averaging (IFWA) operator is used in aggregating decision makers’ preferences for both the criteria set and the alternative ratings. The IFWA operator by Xu (2007) is preferred in this paper because it is simple yet efficient (Li, 2014). In Equation (9) is the IFWA operator where $S_{ij}$ is the aggregated decision matrix:

$$S_{ij} = \text{IFWA}_\rho \left( S_{ij}^{(1)}, S_{ij}^{(2)}, \ldots, S_{ij}^{(d)} \right) = \rho_1 S_{ij}^{(1)} + \rho_2 S_{ij}^{(2)} + \ldots + \rho_d S_{ij}^{(d)}$$

$$= \left\langle 1 - \prod_{k=1}^{d} (1 - \mu_{ij}^{(k)})^\alpha_k, \prod_{k=1}^{d} \nu_{ij}^{(k)} \right\rangle$$

Step 5. Constructing weighted aggregation of IFS. The next step computes the aggregated weighted intuitionistic fuzzy set by multiplying the weight vector of the criteria set by the aggregated decision matrix obtained in step 4. The weighted decision matrix is expressed below:

$$W \otimes S = \tilde{W}^T \otimes \left\langle \mu_{ij}^k, \nu_{ij}^k \right\rangle = \left\langle \mu_{ij}^k, \nu_{ij}^k \right\rangle$$
Step 6. Determining intuitionistic fuzzy positive $A^+$ and negative $A^-$ ideal solutions. At this stage, the criteria are separated into a so-called benefit and cost criteria. Let $B$ and $C$, respectively represent the benefit and cost criteria. Then $A^+$ which maximizes the cost criteria while minimizing benefit criteria, and $A^-$ that maximizes the benefit criteria and minimizes cost criteria are computed as follows:

$$A^+ = (\mu_{A^+}(x_j), v_{A^+}(x_j))$$

$$A^- = (\mu_{A^-}(x_j), v_{A^-}(x_j))$$  \hspace{1cm} (11)

where:

$$\mu_{A^+}(x_j) = \left( \max_{i} \mu_{A_i}(x_j) \mid j \in B \right), \left( \min_{i} \mu_{A_i}(x_j) \mid j \in C \right)$$  \hspace{1cm} (12)

$$v_{A^+}(x_j) = \left( \min_{i} v_{A_i}(x_j) \mid j \in B \right), \left( \max_{i} v_{A_i}(x_j) \mid j \in C \right)$$  \hspace{1cm} (13)

$$\mu_{A^-}(x_j) = \left( \min_{i} \mu_{A_i}(x_j) \mid j \in B \right), \left( \max_{i} \mu_{A_i}(x_j) \mid j \in C \right)$$  \hspace{1cm} (14)

$$v_{A^-}(x_j) = \left( \max_{i} v_{A_i}(x_j) \mid j \in B \right), \left( \min_{i} v_{A_i}(x_j) \mid j \in C \right)$$  \hspace{1cm} (15)

Step 7. Computing separating measures. The distances $d_{IFS}^+$ and $d_{IFS}^-$, which express the distances of each alternative from $A^+$ and $A^-$ are calculated as shown in Equations (16) and (17), respectively. These distances are computed as intuitionistic sets:

$$d_{IFS}^+(A_i, A^+) = \sqrt{\sum_{j=1}^{m} \left[ (\mu_{A_i}(x_j) - \mu_{A^+}(x_j))^2 + (v_{A_i}(x_j) - v_{A^+}(x_j))^2 + (\pi_{A_i}(x_j) - \pi_{A^+}(x_j))^2 \right]}$$  \hspace{1cm} (16)

$$d_{IFS}^-(A_i, A^-) = \sqrt{\sum_{j=1}^{m} \left[ (\mu_{A_i}(x_j) - \mu_{A^-}(x_j))^2 + (v_{A_i}(x_j) - v_{A^-}(x_j))^2 + (\pi_{A_i}(x_j) - \pi_{A^-}(x_j))^2 \right]}$$  \hspace{1cm} (17)

Step 8. Computing relative closeness coefficient and ranking of alternatives. The relative closeness coefficient also known as relative gaps degree $CC_i$, is used to determine the ranking of the $i$th alternative. This is computed as follows:

$$CC_i = \frac{d_{IFS}(A_i, A^-)}{d_{IFS}^+(A_i, A^+) + d_{IFS}^-(A_i, A^-)}$$  \hspace{1cm} (18)

The highest value of $CC_i$ determines the best alternative implying that the chosen alternative is concurrently closer to $A^+$ and farther away from $A^-$. 

Start-up businesses in a GVC scheme
4. Application
The Government of South Africa has instituted a number of pro entrepreneurial initiatives that is run by the Department of Trade and Industry and the Economic Development department. One of such initiatives is the Technology Venture Capital Fund, a government publicly run VC scheme. The GVC among other things offers seed capital to high potential but early stage technology firms to trigger growth (Government of South Africa, 2015). The fund primarily supports commercialization of technology-focused innovations to help create jobs and wealth for the citizenry (Government of South Africa, 2015; Koekemoer and Kachieng’a, 2002). Since its introduction, the fund has supported many businesses with some relative successes but largely, most businesses failed to achieve commercial success resulting in low capital recovery rates. Rogerson (2004) notes that most government venture scheme for small, medium and micro enterprises fail because often time start-ups that exhibit potential for success are discriminated in favour of start-ups with links to the government. Knoesen (2009), Nattrass and Seekings (2001) and Iheduru (2004) all note that the influence of political, social, racial and tribal affiliations often lead to misappropriation of public funds and therefore need to be curbed to ensure the success of such funds. In what follows, a numerical example showing step by step, how the proposed fuzzy intuitionistic TOPSIS method can be used to evaluate and select start-up businesses under GVC’s such as that operated by the Government of South Africa is presented.

4.1 Step 1. Determining sets of alternatives, criteria, linguistic variables and decision-makers
The first step involves the identification of linguistic variables, linguistic terms, the alternatives and decision makers. Table I lists the 27 sets of criteria deemed relevant to the selection problem. Table II also shows the linguistic terms used in rating both the importance criteria and the alternatives expressed in their IFN format. The numerical example has five start-up businesses and four decision makers.

4.2 Step 2. Determining importance weights of decision-makers
The importance of each decision maker in terms of the weight of his/her ratings are determined using Equation 8. In Table III, the importance weights of each of the four decision makers are presented. We assume the ratings of decision maker 3 carries more weight than the others.

4.3 Step 3. Determining weights of each criterion
The decision makers rate to determine the importance weights of each criterion as shown in Table IV using the linguistic terms in Table II. In Table IV, it is shown that criterion 8, technical qualification is deemed the most important by the decision makers.

It must be noted that for the purposes of simplicity and conciseness, the IFNs are expressed only in their membership (satisfaction) and non-membership (dissatisfaction)
forms. This means, to determine the hesitancy in each instance of an intuitionistic rating, Equation (1) is applied. For example, the hesitancy degree for the aggregated weight for criteria 1 in Table IV could be computed as
\[ \pi = 1 - 0.72 - 0.23 \] which results in 0.05 as the hesitancy degree.

4.4 Step 4. Aggregation of decisions
In this step, the alternative ratings giving in Table V are aggregated using the IFWA operator which is expressed in Equation 9. It must be noted that the aggregation procedure factors the importance of each decision maker in the computation.

4.5 Step 5. Constructing weighted aggregation of IFS
The aggregated decisions are weighted at this stage using the weights assigned to the criteria set. The weighted aggregated intuitionistic fuzzy matrix is computed using Equation (10). The results are as shown in Table VI.

4.6 Step 6. Determining intuitionistic fuzzy positive \( A^+ \) and negative \( A^- \) ideal solutions
The FPIS and the FNIS, defined respectively as \( A^+ \) and \( A^- \), are presented in Equations (19) and (20), respectively. In determining \( A^+ \) and \( A^- \), criteria \((C_{15}-C_{18})\) which fall under

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Table IV. Criterion importance weight

Start-up businesses in a GVC scheme
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Alternative ratings
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the financial characteristics category are considered as costs while the rest of the criteria are designated as benefits:

\[
A^+ =  \\
\begin{bmatrix}
(0.67, 0.28), (0.49, 0.46), (0.58, 0.37), (0.29, 0.67), (0.52, 0.41), (0.27, 0.68), (0.61, 0.34) \\
(0.78, 0.20), (0.69, 0.27), (0.26, 0.69), (0.80, 0.18), (0.52, 0.41), (0.22, 0.75), (0.58, 0.37) \\
(0.19, 0.75), (0.11, 0.86), (0.10, 0.88), (0.02, 0.98), (0.68, 0.28), (0.48, 0.45), (0.56, 0.38) \\
(0.56, 0.36), (0.34, 0.59), (0.76, 0.21), (0.49, 0.45), (0.70, 0.25), (0.52, 0.42)
\end{bmatrix}
\]

(19)

\[
A^- =  \\
\begin{bmatrix}
(0.21, 0.74), (0.24, 0.71), (0.14, 0.82), (0.12, 0.85), (0.24, 0.71), (0.05, 0.93), (0.32, 0.62) \\
(0.35, 0.60), (0.26, 0.69), (0.14, 0.82), (0.57, 0.37), (0.22, 0.73), (0.10, 0.87), (0.27, 0.69) \\
(0.56, 0.38), (0.60, 0.35), (0.53, 0.42), (0.20, 0.75), (0.20, 0.74), (0.37, 0.56), (0.32, 0.63) \\
(0.28, 0.66), (0.20, 0.75), (0.33, 0.63), (0.16, 0.79), (0.28, 0.66), (0.25, 0.70)
\end{bmatrix}
\]

(20)
4.7 Step 7. Computing separating measures
The distance measures of $d_{IFS}$ and $\overline{d}_{IFS}$ are computed from each alternative to the fuzzy positive and negative ideal solutions using Equations (16) and (17), respectively. This results in Table VII. Additionally, the closeness coefficient that ultimately determines the ranking order of the alternatives are calculated using Equation (18). It can be seen that per the numerical example, alternative 4 ($A_4$) happens to be the best start-up business followed by $A_3, A_2, A_5$ and $A_1$ in that order (Figure 1).

5. Conclusion
VC schemes can be considered a game of chance where losses as well as profits are equally possible depending on the performance of the start-up business. The likelihood of success is even smaller in the case of GVC scheme. This is in part due to the selection of unmerited start-up businesses as a result of political interferences, and lack of models that explicitly consider qualitative factors such as leadership experiences and product qualities in the selection process. More importantly, to be efficient, any decision making model for aiding the selection problem in a GVC scheme must be able to explicitly model uncertainty. This is because the values of the factors upon which a selection is made are not known at the time of selection. The model must also be able to if not eliminate, help mitigate the perceived lack of transparency in a GVC scheme selection process.

To this end, this paper theoretically generates interests in decision models used in VC by building on previous works. More importantly, the paper helps to simplify and bring formalism into selection decision making processes involving start-up businesses in VC financing schemes. The strength of the paper is the confidence it evokes in the

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<th>$D_-$</th>
<th>$CC_i$</th>
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<td>1.439</td>
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<td>3</td>
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<tr>
<td>$A_3$</td>
<td>1.153</td>
<td>4.107</td>
<td>0.637</td>
<td>2</td>
</tr>
<tr>
<td>$A_4$</td>
<td>0.976</td>
<td>3.752</td>
<td>0.665</td>
<td>1</td>
</tr>
<tr>
<td>$A_5$</td>
<td>1.756</td>
<td>1.409</td>
<td>0.403</td>
<td>4</td>
</tr>
</tbody>
</table>

Table VII. Relative closeness coefficient and ranking

Figure 1. Ranking of start-up businesses (alternatives)
final selection decision by combining all criteria, be it a “more is better” or a “less is better” criterion into a composite score for the start-up candidates. Currently, almost all the decision making models proposed in literature either resort to only quantitative factors, ignore uncertainty by relying on past data or consider uncertainty only in the weights assigned to decision makers. Uncertainties in future values are largely ignored. The proposed method addresses the uncertainty issues through the use of intuitionistic fuzzy TOPSIS method. The issues of fairness and transparency are also known to be a major reason for the underperformance of government-run VC schemes. By its design, the proposed model is able to enhance fairness and transparency in the selection process by demanding decision makers to rate their decisions using linguistic variables that are easy to track for its veracity. This is done by determining the level of satisfaction, dissatisfaction and hesitancy in each decision maker’s assessment or rating of a candidate.

The practicality of the proposed method is demonstrated using an example centred on a government-run VC scheme. The proposed model makes it feasible to include important criteria such as “societal impact/contribution” that are difficult to model analytically in the selection process. As a practical implication, when all necessary parameters are supplied, the proposed model by its design makes the selection process transparent and fair, thereby limiting political influences that are difficult to prevent in PVC’s.

The limitation of the paper is that the set of criteria proposed in this paper may not be exhaustive for adequate selection of technology start-ups in a GVC programme in some jurisdictions around the world. In view of this, the proposed set of criteria may be tinkered with or tailored to suit the decision problem at hand when such need arises. Additionally as is the case in all models for uncertain situations, many of the parameters for analyzing start-ups are future values that are uncertain today. As such management are encouraged to validate the result given by the proposed model.

Future work would compare the performance of the proposed decision aiding framework with other MCDM models. In particular, this model is largely a compensatory model where an inferiority or superiority in a criterion is compensated for or balanced with an inferiority or superiority from another criterion. In future studies, other non-compensatory methods could be compared with our proposed model to ascertain their effectiveness to such decision problem.

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Further reading


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