Internal Auditor Selection using a TOPSIS/Non-Linear Programming Model

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Abstract

One of the most challenging problems in personnel selection is the multi – attribute nature of the candidates. This problem is magnified in the procedure of selection of sophisticated personnel such as internal auditors. By definition, an internal auditor must combine a selection of analytical and non-analytical skills, corresponding to specific cognitive and behavioral attributes. In this paper, a framework for internal auditors' selection using TOPSIS technique is proposed, integrating behavioral and cognitive skills. AHP technique has been used to determine the weights on each criterion. By assigning different importance to the later skills, the proposed framework can identify employable and potentially employable candidates. Besides the desirable skills, in the process of personnel selection, the expected performance is also considered. To examine what would be the ideal importance on cognitive and behavioral skills that maximizes candidates' performance, a Non – Linear Programming Method is applied. A real life application is demonstrated to a sample of internal auditors from a multi-national company.

Keywords: Internal Auditor Selection, Skills, AHP, TOPSIS, Non – Linear Programming

1. Introduction

The personnel selection has so far concerned many researchers and in the relevant literature a compilation of studies can be found. In this context, the personnel evaluation problem can be applied in every professional sector and industry. Simultaneously, the rising importance of corporate governance over the past years highlighted the internal audit function and resulted in a high demand for skilled and efficient internal auditors and auditing quality (Johnson, Reichelt & Soileau, 2018; Ferramosca, D'Onza &Allegrini, 2017; Mihret, & Grant, 2017). Thus, the internal auditors' selection is of great importance and attracts the research interest.

Internal auditing is defined as *an independent, objective assurance and consulting activity designed to add value and improve an organization's operations, which helps organizations to accomplish their goals* (Cascarino, 2007; Smith, 2016).The role of internal auditors is to help the organization to discipline to legislation frameworks and minimize risk and improve governance processes (Hayes, 2017).The responsibilities of an internal auditor normally fit in many different multi-discipline areas of an organization (Raiborn, Butler, Martin & Pizzini, 2017). Therefore, the subject of an internal auditor is extremely complex and demands personnel with specific characteristics combining technical, non-technical skills and qualitative skills, among which, integrity, agility, objectivity, being unaffected and insightful (Seol, Sarkis & Wang, 2017; Lenning, & Gremyr, 2017; Narkchai &Fadzil, 2017; Parker & Johnson, 2017; Abbott, Daugherty, Parker & Peters, 2016; Smith, 2016).

The nature of the profession of an internal auditor combines multiple aspects of different skills, many of which cannot be easily quantified, thus the problem of internal auditors' selection differs in a high degree from the selection of personnel of any other profession (Cai & Jun, 2018).

Due to the multiple nature of the desired skills an internal auditor should have, recruitment of an internal auditor requires a methodology that would take into account qualitative characteristics of a candidate as well. The qualitative data, needed to evaluate an internal auditor, concern a wide selection of non-quantifiable criteria related to professional skills such as critical thinking, problem solving, adjustability to situations, logical reasoning and personal skills such as being honest, open-minded, competitive, and can communicate his/her ideas to other colleagues (Smith, 2016). The methodologies that are suitable for the selection of internal auditors stem from multi-criteria decision analysis area since they can examine alternatives by aggregating criteria.

So far, extended research has been conducted focusing on auditors' recruitment as well as extra emphasis has been put on the auditors' characteristics that affect organizational performance. However, the selection of internal auditors using multi-criteria decision analysis methods under the criteria of cognitive, behavioral skills and performance has not been extensively investigated according to relevant literature.

In this paper a framework for internal auditors' selection using TOPSIS technique is proposed, integrating behavioral and cognitive skills. The use of TOPSIS technique is recommended since the technique is constructed upon finding the minimum distance between the examined and an ideal solution. Furthermore, in order to examine what would be the ideal importance on cognitive and behavioral skills that maximizes candidates' performance a Non – Linear Programming Method is applied. The proposed framework combines behavioral and cognitive skills with internal auditors' expected performance providing a goal-oriented perspective in personnel selection.

The rest of the paper is organized as follows: In Section 2, the literature review discusses previous research on auditors' characteristics and performance and on methodologies applied in personnel selection procedure. Then, the proposed model is presented in Section 3 demonstrating the theoretical framework applied to a real life situation. The results of the model and the data are presented in Section 4 and the paper concludes in Section 5.

2. Literature Review

2.1 Auditors' characteristics and performance

The increasing demand for highly skilled and efficient internal auditors raises the issue of auditors' recruitment processes and the relevant applied methodologies. The recruitment is a triple procedure including the definition of the objectives, the evaluation and ranking of the candidates. In this context, a typical model for the organizational recruitment process may be applied, since it incorporates sophisticated and applied tools which fit to the nature of the internal auditors' profession.

The auditors' profession, by definition, demands special personal attributes which are not easily measured or captured, such as ethics, independence and objectivity. Besides the personal skills, the international standards for the professional practice of the internal auditing set the essential guidelines. Also, the audit activity and the responsibilities of internal auditors set a group of technical and organizational skills (IPPF, 2013).

In the literature, the distinction between the concepts of personal characteristics and the attributes that stem from the professional expectations and requirements set two main groups of skills: cognitive skills and behavioral skills. The cognitive skills include technical skills, analytic/design skills and appreciative skills, while the behavioral skills include personal skills, interpersonal skills and organizational skills (Bailey, Gramling & Ramamoorti, 2013; Gramling & Ramamoorti, 2003, Seol & Sarkis, 2005, Seol, Sarkis & Lefley, 2011).

Lenz and Hahn (2013) revised Bailey, Gramling & Ramamoorti (2003) model by introducing: a) the relationship between internal auditor and the rest of the staff, the senior management and the board, b) understanding and appreciation of procedures, c) personality, d) micro factors (organizations) and e) macro factors including coercive force, adherence to the professional practices and mimetic force. Furthermore, Sanusi et al. (2018) highlighted the importance of psychological constructs in terms of auditors' judgment performance based on the learning goal orientation and self-efficacy.

In an attempt to improve auditing quality several frameworks have been proposed (PCAOB, 2015a, Knechel et al., 2013), highlighting the importance of three elements: audit professionals, audit process and audit results while several auditing quality indicators have been proposed. Towards the measurement of audit professionals, the proposed quality indicators include technical competence, due professional care, ineffective engagement quality reviews, persons with specialized skills and knowledge, industry expertise of audit personnel, experience of audit personnel and interpretation or application of law and standards requirements (PCAOB, 2015a).

The changes in social, economic and technological environment highlight the need for adaptation of skills. These trends bring to the surface the importance of competence (Kabuye et al, 2017), IT skills (Bierstaker, Janvrin & Lowe, 2014) and communication skills in the different organizational procedures, including auditing. Auditors need to be communicative in all the situations they encounter, enhance their interpersonal skills and be aware about the impact of their mannerisms to the organization (Gene, 2005). Similarly, low quality in internal control, stemming from lack in skills (IT expertise) may have negative impact on the performance of the organization (Haislip, Petersb & Richardson, 2016).

Another important factor in the recruitment process, besides auditor's skills, is the determination of the desired auditor's performance. It has been noticed that there are differences in the perception of various stakeholders considering the drivers of internal audit effectiveness and the identification of performance measures (Erasmus & Coetzee, 2018). The Public Company of Accounting Oversight Board presents auditors' results and performance as a quality segment, indicated by frequency and impact of financial statement restatement for errors, fraud and other financial reporting misconduct, financial reporting quality, timely reporting of internal control weaknesses, timely reporting of going concern issues (PCAOB, 2015a). Among the measures applicable for auditing performance, convergence of/deviation from the set of goals and coverage of required level of competence (professional, organizational and managerial skills), developing, implementing and using organizational tools and techniques, adaptability (Cullen et al., 2014) employee engagement and commitment and personal development (Anitha, 2014) are derived.

Several studies revealed that auditors' personal attributes and performance affect organizations in a wide variety of aspects. D'onza et al (2015) support that effective internal auditors add value to their organizations. Mubako and Mazza (2017) found that organizational turnover may be affected by the internal auditor experience and the staff level. Muttakin, Khan and Mihret (2017) revealed that the level of discretionary accruals is positively associated with business group affiliation status while higher audit quality reduces this association. Lin (2018) concluded that auditors' incentive-based compensation is negatively correlated to accruals quality and positively connected with abnormal audit fees. Elliott, Dawson and Edwards (2007) highlighted organizational deficiencies as part of compliance to standards (such as ISO 9001) that stem from the fact that internal audits are not always well received and they lack in performance. Penalties and organization inefficiencies are commonly the results of audit failure, which is proved to be related to auditors' experience and education (Ye, Cheng & Gao, 2014), while high internal organizational status and high level of internal audit competence may predict fraud management (Kabuye et al, 2017). In the context of corporate governance and compliance with the international financial standards, studies revealed that auditors' independence, expertise in accounting and in special industry promote the standards' adoption and application (Sellami &Fendri, 2017). Finally, the internal auditing contributes to the accomplishing of the targeted objectives by the entity (Danescu, Prozan & Prozan, 2015).

Furthermore, the auditor's gender seems to influence organizational performance according to Khlif and Achek (2017). In their review, they make obvious that female auditors influence several accounting phenomena including earnings quality, reporting policy, audit quality and analyst forecast accuracy.

On the contrary, the relation between governance and internal auditors has proved to be bidirectional, as not only the auditors affect the organizational performance, but the opposite stands as well. In their study, Houqe et al (2015) revealed that firms in countries with high respect to corporate governance and ethical values are more likely to hire an established auditor and that reporting quality is indirectly linked to corporate ethics. The effectiveness of auditors may also be affected by the national culture and the degree of corporate governance maturity (Brender, Yzeiraj & Fragniere, 2015). The cultural factors affect the internal auditors' professionalism, independence and uniformity of practice and may also reduce training, skills and knowledge (Al-Akra, Abdel-Qader & Billah, 2016). Ballesta and Meca (2005) underlined the effect of governance on audit qualifications, opinions and reports and Alzebana and Sawan (2015) revealed that the presence of independent members of the audit committee and their expertise in accounting and auditing affects the implementation of internal audit recommendations and performance. Finally, Hassan, Hijazi and Naser (2017) pointed that corporate governance mechanisms may contribute and enhance auditor performance. Recent studies reveal that technical knowledge deficiencies, burnout, multitasking, reliance on outside work (Veena et al, 2016), work stress (Yan & Xie, 2016) may affect the excellence in auditing performance and quality.

Besides the governance, other factors may influence auditors' performance such as the complex legislative design (Michael & Williams, 2018), the relationship between internal and external auditors (Alzeban & Gwilliam, 2014) and job satisfaction (Dali & Mas'ud, 2014).

In view of all this, it is clear that the current literature lacks a comprehensive personnel selection framework that considers both the employees characteristics and their performance. So far, the auditors' selection problem has been approached either by highlighting the auditors' characteristics or by summarizing the effects of auditor performance on business. The need to further explore such a promising but still unchartered territory of research is an undeniable fact. A TOPSIS model that could rank different candidates setting distinctions among them, based on specific cognitive and behavioral skills selected by the HR department that take into account their performance, can most probably fill the current literature gap.

3. Research design

3.1. Personnel Selection

A variety of methodologies have been applied to personnel selection and evaluation problem. Among these methodologies, MCDM methodologies are used in order to select, evaluate and rank candidates with often conflicting characteristics. The applied MCDM methods include the Analytic Hierarchy Process (AHP), the technique for order preference by similarity to ideal solutions (TOPSIS), the VIsekriterijumskaOptimizacijaiKOmpromisnoResenje: multicriteria optimization and compromise solution (VIKOR), ELimination Et Choix Traduisant la REalit´e: ELimination and Choice Translating Reality (ELECTRE II), Preference Ranking Organization METHod for Enrichment Evaluation (PROMETHEE II), Data Envelopment Analysis (DEA), expert systems (ES), and Analytic Network Process (ANP). Since the main problem in human resources selection is fuzziness, which stems from the difficultly that decision makers face in the process of assigning scores to candidates' characteristics in order to evaluate and rank them, the MCDM methods are often extended to the fuzzy environment combing the fuzzy set theory (Afshari, Nikolić & Ćoćkalo, 2014; Mardani, Jusoh & Zavadskas, 2015).

The application of TOPSIS in the HR field and more specific in the selection of staff has been widely used. The method has been widely applied by researchers in the personnel selection procedures in many and different alterations and extensions. Shih, Shyur& Lee (2007) extended TOPSIS by integrating a multi-attribute decision making technique taking into account that there are more than one decision makers with different preferences and applying the proposed model in the procedure of staff selection; Kelemenis & Askounis (2010) have incorporated a concept based on the veto threshold in the ranking of candidates; the relative importance of each criterion by the decision makers and the degree of similarity and proximity among them have been introduced in the TOPSIS by Kelemenis, Ergazakis and Askounis (2011); Sang, Liu and Qin (2015) proposed a fuzzy TOPSIS method based on Karnik–Mendel algorithm keeping computational efficient and avoiding information loss. Moreover, the TOPSIS has been combined with other techniques or method in the process of the relative weighting of hierarchical criteria, such as Structural Equation Modelling (SEM) (Karaveg, Thawesaengskulthai&Chandrachai, 2015), the Hungarian Assignment Algorithm (Safari, Cruz-Machado, Sarraf&Maleki, 2014), Fuzzy Analytical Hierarchy Process (Kusumawardani & Agintiara, 2015, Erdem, 2016, Mediouni et al., 2018) and the principles of fusion of fuzzy information and 2-tuple linguistic representation model (Dursun & Karsak, 2010).

The fuzzy VIKOR method is applied in problems that require the selection from a set of different solutions or alternatives in a fuzzy environment and their ranking close to the ideal. As a methodology, it has been applied in personnel selection and evaluation problems in cases where the decision maker is not able to express preference in the first steps of the system design. For solving the problem of personnel selection and evaluation of overall performance taking into account a set of information culture criteria an integrated fuzzy MCDM approach has been proposed. In their study Alguliyev, Aliguliyev and Mahmudova (2015), after the determination of the evaluation criteria, the problem of personnel evaluation was approached by means of modified VIKOR under a fuzzy environment. The relative weight of each criterion was determined by applying the "worst case" method and the ranking of alternatives was approached based on the modified fuzzy VIKOR method. Another algorithm that has been applied in the process of staff selection is ELECTRE (Rouyendegh & Erkan, 2012, And Wu and Chen, 2011, Afshari et al, 2010).

Amongst the different MCDM methods and models applied in personnel evaluation and selection several combinations have been proposed such as: a combination of stepwise weight assessment ratio analysis (SWARA) and grey additive ratio assessment (ARAS-G) methods (Heidary Dahooie et al, 2018); the application of Fuzzy ARAS and Fuzzy MOORA (Multi-Objective Optimization on basis of Ratio Analysis) which are integrated through group decision making (GDM) method (Bos & Chatterjee, 2016); combination of the additive ratio assessment method with fuzzy numbers (ARAS-F) and the AHP (Keršulienė & Turskis, 2014); a framework composed of fuzzy ANP, fuzzy TOPSIS and fuzzy ELECTRE methods (Kabak, Burmaoğlu & Kazançoğlu, 2012); the extensions of MOORA (Baležentis, Baležentis & Brauers, 2012); a combination of analytic network process (ANP) and PROMETHEE with the visual techniques of graphical representation of actions evaluated on two criteria (GAIA plane) and the stacked bar chart (Ishizaka & Pereira, 2016); an integration of Delphi method, a Fuzzy Decision Making Trial and Evaluation Laboratory (DEMATEL) and Fuzzy Analytic Network Process (ANP) method (Aghaee & Aghaee, 2016).

The Analytic Hierarchy Process has also been applied in personnel selection problems (Pant et al., 2014, Manoharan, Muralidharan & Deshmukh, 2011, Aggarwal, 2014, Güngör, Serhadlioğlu & Kesen, 2009). Other approaches in literature towards personnel selection, evaluation and ranking include the application of amalgamated fuzzy systems, ANNs, Genetic algorithms (Rashidi, Jazebi, & Brilakis, 2010), the use of Hamming distance method (Saad et al., 2014) and decision support tools using an integrated analytic network process (ANP) and fuzzy data envelopment analysis (DEA) (Lin, 2010).

3.2 Proposed Model

The proposed model extends the work of Seol & Sarkis (2005), considering extra criteria, as described in Table 1,and applying TOPSIS methodology for the multiple attributes, behavioral and cognitive for internal auditor selection. As seen in the literature, the majority of the papers that present multicriteria decision analysis techniques for internal auditors' selection do not examine the robustness of the solution which is important since the weights assigned or derived (from pair wise comparisons) are subjective.

The contribution of the proposed framework is threefold. Firstly, scenarios are examined for multiple weight combinations on each aspect (cognitive and behavioral) based on which internal auditors will be ranked upon. In conjunction with the score of each internal auditor to each criterion, different weight representations lead to different internal auditors' ranking providing better discrimination between employable candidates, quasi – employable candidates and non-employable candidates. Secondly, in this paper, a new score is proposed considering the performance which also plays a significant role in the internal auditors' selection. Finally, to investigate the link between high performance and the optimal weights of candidates' cognitive and behavioral skills, a Non-Linear Programming Model is proposed. The proposed approach is a new framework for selecting internal auditors by correlating candidates' skills with their expected performance. It also should be mentioned that despite the fact that the presented case study refers to internal auditors, the proposed approach may be applied in any employee selection problem. Both the theoretical background and the combination of TOPSIS/Non-Linear Programming Model are novel to the relevant literature.

Table 1: Top and bottom level criteria for Internal Auditors' (IA) selection.

Cognitive skills		
Technical skills	**Analytic/Design problem structuring and solving skills**	**Appreciative skills judgment / synthesis**
T 1. Using information technology – audit software	AN 1. Analyzing commercial and financial data	APP 1. Finding all that is relevant
T 2. Apply control system designs and procedures	AN 2. Basic analysis of accounts and accounting reports	APP 2. Risk awareness
T 3. Apply laws and regulations	AN 3. Internal audit requirements analysis/definition	APP 3. Seeing anomalies and recognizing their implications
T 4. Apply internal auditing technologies and procedures	AN 4. Using non-financial evaluation methods in internal audit work	APP 4. Interpreting relevant laws and standards
T 5. Documentation of internal audit work	AN 5. Developing prototype solutions to problems	APP 5. Managingcomplexity

Behavioral skills		
Personal skills	**Interpersonal skills**	**Organizational skills**
PER 1.Decisive	INT 1. Communication – persuasiveness	ORG 1. Adapting internal audit work to a wide range of organizational systems, methods, and standards
PER 2.Dedication	INT 2. Influencing, persuading, motivating, changing others	ORG 2. Scheduling
PER 3.Intuitive/gut-feel	INT 3. Handling multi-tasking	ORG 3. Attaining a knowledge of the business (products, strategies, processes, markets, risks)
PER 4.Proactive	INT 4. Leaderships – of teams, groups	ORG 4. Finding way around organizations
PER 5.Professional demeanor	INT 5. Facilitation	ORG 5. Building trust

Performance (*based on HR department suggestion*)	
Goal Oriented	**Coverage of required level of competence (professional, organizational and managerial skills)**
GOAL 1. Achievement of quality objectives	COMP 1. Provide accurate problem solutions
GOAL 2. Achievement of quantitative objectives	COMP 2. Adaptability
	COMP 3. Application of Law and Standards
	COMP 4. Adherence to administrative procedures
	COMP 5. Developing, implementing and using organizational tools and techniques

3.3. Mathematical formulation

In this section, the mathematical formulation of the paper is presented. Since the selection of an internal auditor is complex as the decision maker has to examine different, often conflicting criteria, the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) method is applied. The advantages of TOPSIS technique lie on the fact that it is very simple to construct the problem, it is easily comprehensible and demonstrates adequate computational efficiency since allows the weighting of each criterion (regardless of the level) from the decision maker. Also, TOPSIS provides a scalar value that accounts for both the best and worst alternatives ability to measure the relative performance for each alternative in a simple mathematical form while the results can be easily plotted.

On the contrary, Analytical Hierarchy Process (AHP) can be potentially applied to the problem of personnel; however, an increase of the size of the problem will lead the decision maker(s) to meaningless pairwise comparisons among criteria.

In this paper TOPSIS method is selected based on the aforementioned reasons. Also, the advantages of AHP are utilized since AHP technique is used for determining the weights on top and bottom level criteria.

Assuming that there are i alternatives and j criteria. Initially, the matrix of scores per alternative i and criterion$j$ is denoted with $x_{i,j}$. The scores of the matrix $x_{i,j}$ can express either benefit functions which is approximated by an increasing scale (small values are worse, large values are better) or by cost functions which is approximated by decreasing values (large values are worse while small values are better). The structure of the problem is formulated in a hierarchical form, as shown in Figure 1.

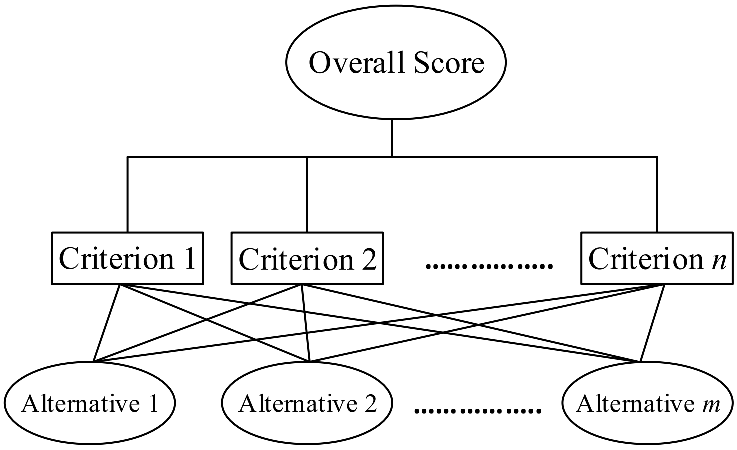


Figure 1: Typical hierarchical structure of multi-criteria decision problem.

According to Figure 1, each alternative is ranked based on weightage of the criteria of the problem. The structure of the hierarchy may consist of multiple levels of criteria. The criteria that are placed on the upper level are called upper level criteria while the second layer consists of the bottom level criteria.

Assuming that A_i are potential alternatives (internal auditors) and C_j are criteria based on which the alternatives will be ranked upon. Having defined some basic terms, the TOPSIS technique consists of the following steps:

Step 1. Construct the decision matrix and weights of criteria: Since the scores of each alternative to each criterion can potentially receive any value, then the following stands for decision matrix $x_{i,j} \in \mathbb{R}$. Also, the preference or the relative importance of each criterion is expressed with weights $(w_j, j = 1, \dots, n)$ such that $\sum_{j=1}^{n} w_j = 1$.In additive techniques like TOPSIS, weights represent value trade-offs among criteria.

Step 2. Normalized decision matrix calculation: It is common that the alternatives in the decision matrix $x_{i,j}$ cannot be compared against each other due to difference in units of measurement. In order to override this obstacle, the scores of the decision matrix are normalized, yielding non-dimensional attributes.

There are multiple methods for obtaining normalized scores ($n_{i,j}$) of decision matrix ($x_{i,j}$) which are the following (if the scores of the decision matrix are expressed by a benefit function):

a. $n_{i,j} = \frac{x_{i,j}}{\sqrt{\sum_{j=1}^{n} x_{i,j}^2}}, i = 1, \dots, m, j = 1, \dots, n$

b. $n_{i,j} = \frac{x_{i,j}}{max_i(x_{i,j})}, i = 1, \dots, m, j = 1, \dots, n$

c. $n_{i,j} = \frac{x_{i,j} - min_i(x_{i,j})}{max_i(x_{i,j}) - min_i(x_{i,j})}, i = 1, \dots, m, j = 1, \dots, n$

Step 3. Calculation of the weighted normalized decision matrix: Since each criterion does not have the same relevant importance, the normalized matrix ($n_{i,j}$) is multiplied with the corresponding weight (w_j) expressed with the following formula:

$$v_{i,j} = w_j \times n_{i,j}, i = 1, \dots, m, j = 1, \dots, n$$

Step 4. Calculation of positive ideal and negative anti-ideal points: Due to the multi-criteria nature of the problem, the alternatives can exhibit extreme performance on a criterion (positive ideal point) or reverse extreme performance on a criterion (negative ideal point). The positive ideal point is expressed as follows:

a. **Positive ideal point**: $v_j^+ = max_i(v_{i,j}), j = 1, \dots, n$

b. **Negative anti-ideal point**: $v_j^- = min_i(v_{i,j}), j = 1, \dots, n$

Step 5. Calculation of distance (separation measures) from ideal and anti-ideal point: For each of the aforementioned cases (ideal and anti-ideal points), the distance of each normalized score of alternative i is calculated using the following formulas:

a. **Separation of each alternative from the positive ideal point**:

$$d_i^+ = \left(\sum_{j=1}^{n} \left(v_{i,j} - v_j^+ \right)^p \right)^{1/p} , j = 1, \dots , n$$

b. Separation of each alternative from the negative anti-ideal point:

$$d_i^- = \left(\sum_{j=1}^{n} \left(v_{i,j} - v_j^- \right)^p \right)^{1/p} , j = 1, \dots , n$$

The Minkowski distance (or separation) measures as formulated above, turn into Euclidean distance for $p = 2$, while for $p = \infty$it is transformed as follows:

$$d_i^+ = max_j |v_{i,j} - v_j^+|$$

$$d_i^- = max_j |v_{i,j} - v_j^-|$$

Step 6. Calculation of relative distance to positive ideal position: The overall score for each alternative i is calculated with respect to d_i^+ and d_i^- as follows:

$$R_i = \frac{d_i^-}{d_i^- + d_i^+}, i = 1, \dots , m$$

For each alternative i, $0 \leq R_i \leq 1$, while the alternatives are ranked based on the values of R_i in a descending order.

In most cases, a single level of criteria is not realistic. In this case, the hierarchical structure consists of top level criteria (Criteria A, and B) and bottom level criteria (Criterion 1,…,Criterion *n*-1, Criterion *n*) as shown in Figure 2.

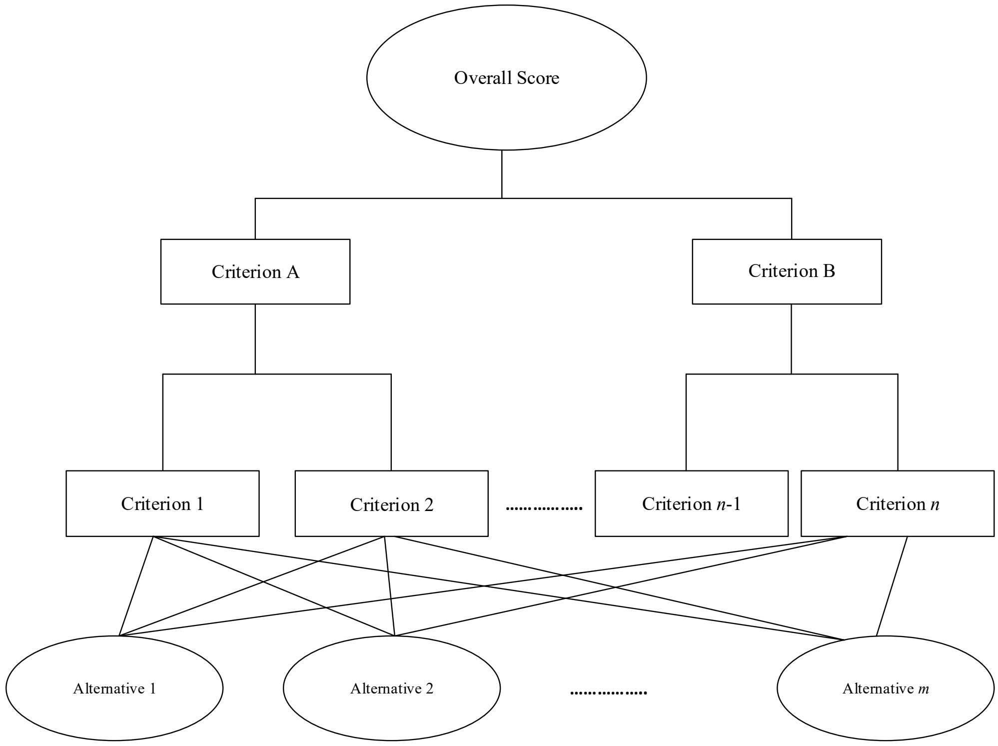


Figure 2: Typical hierarchical structure of multi-criteria decision problem with multiple levels of criteria.

Since the formulation of TOPSIS as described above, is applied to specific criteria, the overall score of the top - level criteria is calculated as follows:

$$R_i^{OV} = \sum_{k=1}^{K} w_k^{up} \cdot R_{k,i} , i = 1,..,m \tag{1}$$

In (1), R_i^{OV} is the overall score of alternative$i$ defined as the sum of product the top level criteria with the scores derived from TOPSIS method (R_i). Top level criteria can be either set directly or can be calculated based on pairwise comparisons from AHP (Kelemenis & Askounis, 2010).

3.4 Sensitivity analysis

In MCDM methodologies, sensitivity analysis is very important since the output (ranking of alternatives) is often based on subjective data. These data concern either judgments of decision makers regarding the alternatives or weights on each criterion (both top and bottom level). To check the robustness of the solution, different scenarios on criteria can be applied. Consequently, each scenario realization will lead to non-unique ranking allowing the decision maker to examine the range of weights for which each alternative becomes first, second and so on.

Assuming that $s\,(s = 1,..,S)$ is the set of scenarios, then for different scenarios on either upper of bottom level criteria, then the corresponding overall score ($R_{i,s}^{OV}$)of alternative i for each weight scenario s, is calculated as follows:

$$R_{i,s}^{OV} = \sum_{k=1}^{K} w_{k,s}^{up} \cdot R_i, s = 1,..,S,, i = 1,..,m \qquad (2)$$

4. Application to Internal Auditors' selection problem

As discussed in the previous sections, the problem of selecting an Internal Auditor is complex since several criteria covering all aspects of the individual have to be taken into consideration. Despite the large amount of available criteria, in the current case study, specific criteria regarding the internal auditors' characteristics have been selected following the Human Resources Department proposal. More specifically, three HR managers proposed the selected criteria as must-be criteria in the selection problem.

The relevant literature separates the criteria of internal auditor selection into two large categories of skills, namely cognitive and behavioral. The first category of skills is further analyzed into Technical, Analytic (problem structuring and solving) and Appreciative skills.Expect for cognitive skills, another important category for internal auditor selection is the behavioral skills. This category of skills emphasizes more on factors that concern the personality of the individual and are further analyzed to Personal, Interpersonal and Organizational skills, as shown in Table 1.

The structure of the problem graphically is shown in Figure 3.

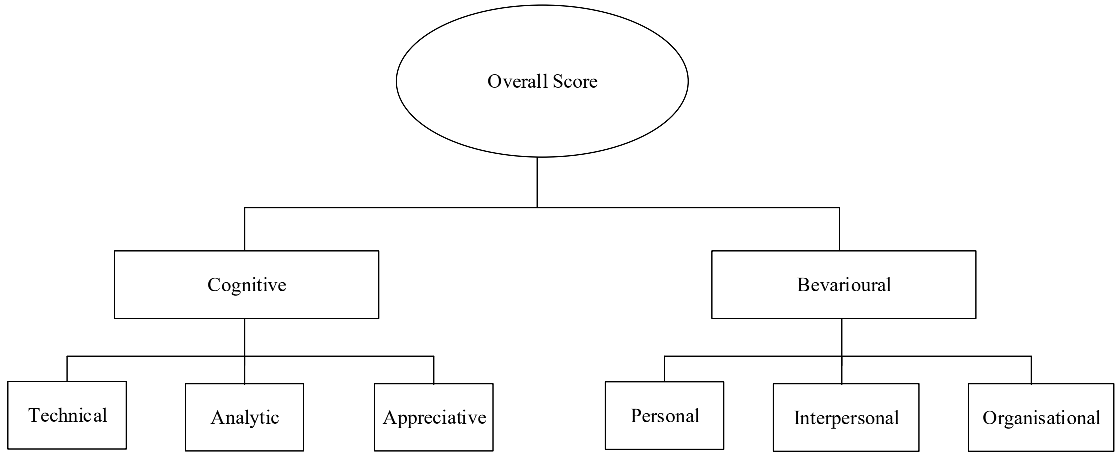
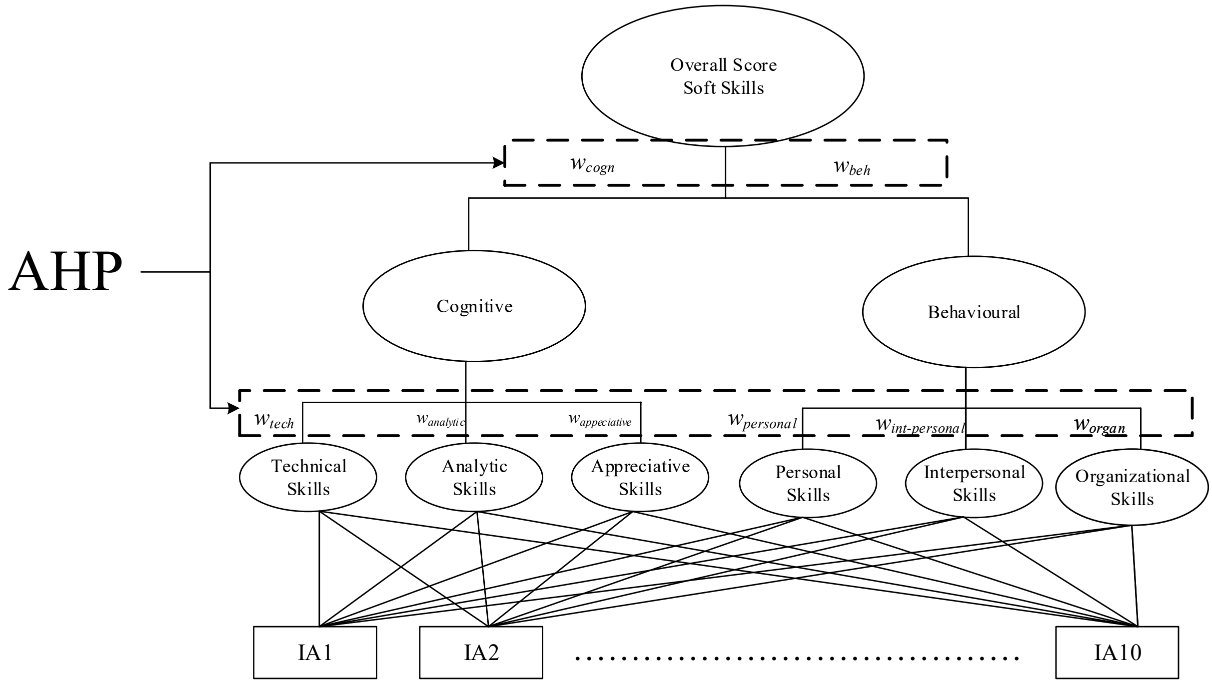


Figure 3: Hierarchical structure of the proposed model

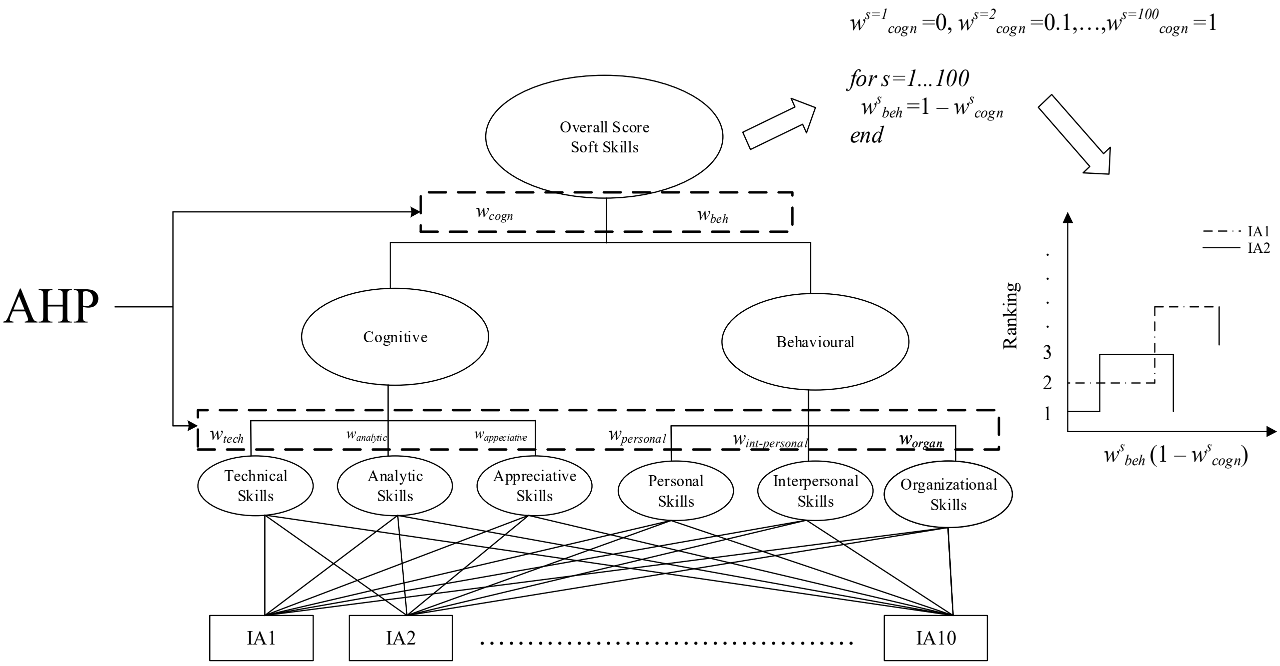
Another factor that plays an important role to the selection of an Internal Auditor is performance. According to HR department and based on their experience, performance criterion consists of two sub-factors namely goals and competency (as shown in Table 1).

The methodology of the paper is graphically illustrated in Figure 4. Firstly (Figure 4 a), the TOPSIS model is to rank internal auditors based on cognitive and behavioral criteria. The weights on top-level and bottom-level criteria are derived using AHP technique. Secondly, scenarios are examined for weights of top-level criteria examining the ranking of internal auditors categorizing them as employable, quasi-employable and not employable (Figure 4 b). Finally, a NLP model is formulated minimizing the Euclidean distance between the scores derived based on cognitive and behavioral skills and the performance dimension (Figure 4c).



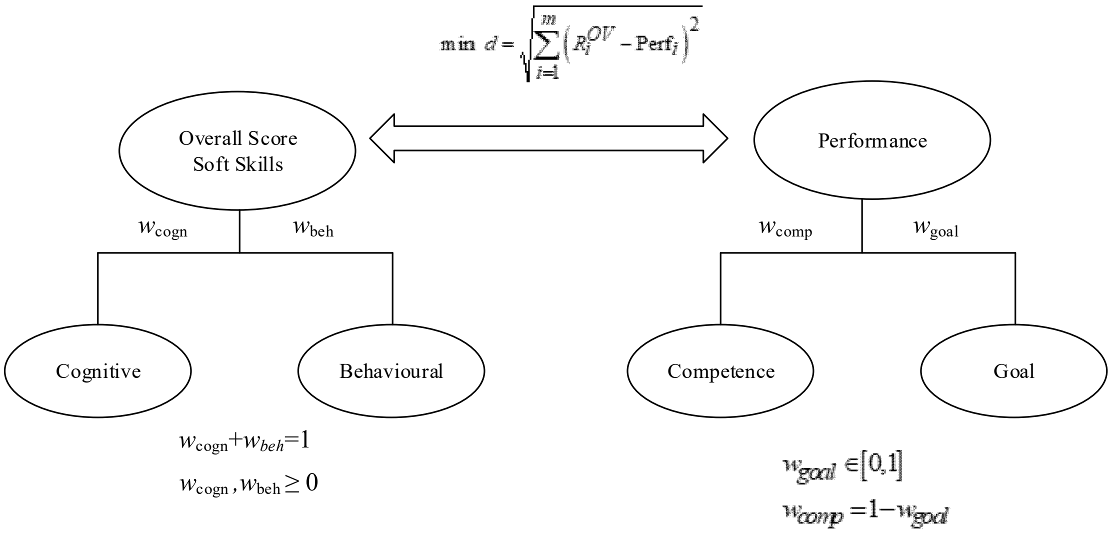
Overall Score
Soft Skills
w_{cogn}
w_{beh}
AHP
Cognitive
Behavioural
w_{tech}
$w_{analytic}$
$w_{appeciative}$
$w_{personal}$
$w_{int\text{-}personal}$
w_{organ}
Technical Skills
Analytic Skills
Appreciative Skills
Personal Skills
Interpersonal Skills
Organizational Skills
IA1
IA2
IA10

(*a*)



$w^{s=1}{}_{cogn}=0, w^{s=2}{}_{cogn}=0.1,\ldots,w^{s=100}{}_{cogn}=1$
for s=1...100
$w^{s}{}_{beh}=1-w^{s}{}_{cogn}$
end
Overall Score
Soft Skills
w_{cogn}
w_{beh}
AHP
Cognitive
Behavioural
w_{tech}
$w_{analytic}$
$w_{appeciative}$
$w_{personal}$
$w_{int\text{-}personal}$
w_{organ}
Technical Skills
Analytic Skills
Appreciative Skills
Personal Skills
Interpersonal Skills
Organizational Skills
IA1
IA2
IA10
IA1
IA2
Ranking
1
2
3
$w^{s}{}_{beh}\,(1-w^{s}{}_{cogn})$

(*b*)



(*c*)

Figure 4: Graphical illustration of the proposed methodology: a) TOPSIS formulation with weights derived from AHP technique, b) scenario formulation for cognitive and behavioral skills, c) NLP model minimizing distance between two TOPSIS models.

4.1 Application data

The data of the problem are shown in Tables (2 – 7). For each alternative, a continuous score between 1 (lower value) and 10 (higher value) of each alternative (internal auditor) to each criterion. In this study, 10 internal auditors (IA1,…,IA10), have been selected from a multi-national company from the branch of Greece. Both the name of the company and the name of the Internal Auditors have been anonymized. The scores presented in the following tables represent the average values of the company's HR board for each internal auditor to each criterion.

Table 2: Scores of Internal Auditors to Technical skills.

	T1	**T2**	**T3**	**T4**	**T5**
IA1	2.55	8.59	5.95	3.71	3.63
IA2	3.02	4.15	8.71	1.60	5.50
IA3	9.98	6.21	9.92	7.86	2.18
IA4	6.76	2.44	3.25	7.02	4.92
IA5	4.24	4.16	2.18	2.35	6.30
IA6	8.48	3.08	6.99	7.98	3.73
IA7	1.99	5.52	2.44	8.85	3.39
IA8	3.57	6.35	7.50	6.65	5.17

IA9	4.72	2.06	3.83	1.42	4.05
IA10	2.64	6.81	6.05	7.93	3.68

In Table 2, the scores of each Internal Auditor are shown with respect to Technical Skills (T1 – T5). It can be seen that IA1 is given a low score in T1 (Using information technology – audit software) which is equal to 2.55 while the largest score is assigned to T2 (Apply control system designs and procedures) which is equal to 8.59.

Similarly, the data for the rest of the skills/criteria (Analytic – problem solving, Appreciative, Personal, Interpersonal, Organizational) are given in Tables 3 – 7.

Table 3: Scores of Internal Auditors to Analytic/Design problem structuring and solving skills.

	AN1	**AN2**	**AN3**	**AN4**	**AN5**
IA1	6.95	7.80	6.65	3.55	1.78
IA2	1.92	6.77	5.91	1.28	8.13
IA3	1.65	2.58	5.73	7.75	2.60
IA4	1.31	6.27	6.59	4.50	4.23
IA5	3.19	3.22	2.17	9.40	4.42
IA6	8.05	3.70	2.13	7.74	1.62
IA7	2.82	1.05	3.43	5.50	2.36
IA8	2.57	3.98	3.85	3.90	9.68
IA9	9.94	4.33	4.36	7.95	4.57
IA10	9.22	2.08	7.62	1.50	6.19

Table 4: Scores of Internal Auditors to Appreciative skills judgment / synthesis.

	APP1	**APP2**	**APP3**	**APP4**	**APP5**
IA1	1.46	1.05	4.61	5.68	6.66
IA2	3.03	4.57	3.48	2.37	9.43
IA3	4.80	2.21	4.47	4.37	3.42
IA4	9.54	2.70	3.68	1.67	4.61
IA5	1.92	4.46	3.92	2.73	2.01
IA6	6.37	5.60	1.41	8.05	9.51
IA7	6.37	6.47	4.26	6.35	7.12
IA8	5.56	2.43	6.91	5.71	2.12
IA9	9.88	3.05	7.08	7.99	9.39
IA10	2.81	3.67	2.78	3.22	6.82

Table 5: Scores of Internal Auditors to Personal skills.

	PER1	PER2	PER3	PER4	PER5
IA1	7.61	1.77	2.35	4.91	2.68
IA2	7.23	7.87	2.39	4.50	7.26
IA3	8.61	6.51	9.78	1.24	2.69
IA4	1.78	5.86	2.14	7.61	2.02
IA5	5.40	8.16	5.43	5.80	1.10
IA6	5.89	5.06	9.78	2.65	2.47
IA7	1.22	2.60	1.55	1.15	8.52
IA8	6.41	1.24	2.76	9.56	4.02
IA9	6.35	3.33	6.77	2.40	5.14
IA10	4.54	8.25	5.87	4.52	6.02

Table 6: Scores of Internal Auditors to Interpersonal skills.

	INT1	INT2	INT3	INT4	INT5
IA1	9.39	4.14	1.07	9.54	6.15
IA2	4.00	9.85	7.90	1.99	9.95
IA3	6.22	2.50	6.79	4.10	9.21
IA4	9.10	1.15	4.32	6.98	6.34
IA5	1.31	8.58	9.39	5.57	3.70
IA6	5.47	1.40	7.96	5.80	7.72
IA7	7.48	6.68	2.03	9.74	7.36
IA8	9.88	8.69	6.59	7.31	7.31
IA9	8.12	6.49	1.49	5.37	1.47
IA10	7.29	2.75	3.03	8.32	9.93

Table 7: Scores of Internal Auditors to Organizational skills.

	ORG1	ORG2	ORG3	ORG4	ORG5
IA1	7.76	7.47	1.01	3.37	8.41
IA2	8.38	8.74	2.91	5.11	1.35
IA3	3.91	4.96	3.84	2.21	8.30
IA4	4.75	2.28	5.19	3.55	9.06
IA5	1.58	4.73	4.07	5.21	6.78
IA6	6.79	4.04	1.91	9.15	2.96
IA7	9.27	5.07	1.81	4.37	4.73
IA8	4.64	2.01	7.76	8.23	1.21
IA9	5.33	3.51	9.11	1.16	7.13
IA10	9.56	9.10	9.09	8.87	4.52

Since the weights represent trade-offs between criteria, providing directly weights may be misleading. In this work, the importance on each criterion has been derived using AHP. Through questionnaires each member of the HR board of the company provided the importance in terms of pairwise comparisons for bottom and top-level criteria (Saaty, 1990). The application of AHP was conducted on the geometrical mean of questionnaires. The weights assigned to each sub-criterion of the cognitive skills are shown in Table 8.

Table 8: Weights for each sub-criterion of cognitive skills.

Technical skills	**weight**
T1	0.2
T2	0.1
T3	0.1
T4	0.3
T5	0.3
Analytical skills	**weight**
AN1	0.1
AN2	0.1
AN3	0.05
AN4	0.55
AN5	0.3
Appreciative skills	**weight**
APP1	0.05
APP2	0.3
APP3	0.2
APP4	0.2
APP5	0.05

The weights assigned to each sub-criterion of the behavioral skills are shown in Table 9.

Table 9: Weights for each sub-criterion of behavioral skills.

Personal skills	**weight**
PER1	0.1
PER2	0.2
PER3	0.3
PER4	0.2
PER5	0.2

Interpersonal skills	weight
INT1	0.15
INT2	0.3
INT3	0.2
INT4	0.15
INT5	0.2
Organizational skills	**weight**
ORG1	0.15
ORG2	0.4
ORG3	0.15
ORG4	0.15
ORG5	0.15

Each sub-criterion is weighted to form a latent structure (Cognitive and Behavioral). More specifically, to form the cognitive skills factors, technical skills are weighted with 40%, analytical skills with 40% and appreciative skills with 20%. Regarding the behavioral skills factor, the personal skills are weighted with 20%, interpersonal skills with 45% and organizational skills with 35%. Finally, both cognitive and behavioral skills are equally weighted to form the overall score of each internal auditor.

The performance aspect, measures the skills of the potential internal auditor in terms of goals (Goal Oriented), and Competence skills (referring to managerial skills of each internal auditor) as shown in Table 1. The data, for each internal auditor to each criterion, are presented in Table 10 and 11. The goal aspect consists of two sub-factors as shown in Table 1. The scores for each factor are given in Table 10 represent the average values of the company's HR board for each internal auditor to each criterion as with the scores computed in the previous section.

Table 10: Scores of Internal Auditors with respect to Goal Skills (Performance).

	GOAL1	GOAL2
IA1	5,54	8,48
IA2	6,42	1,74
IA3	6,20	6,34
IA4	7,15	2,43
IA5	3,99	3,84
IA6	5,68	4,27
IA7	2,51	7,15
IA8	5,55	6,19
IA9	7,48	7,15
IA10	1,18	8,56

The data for the competence sub-factor of performance are presented in Table 11.

Table 11: Scores of Internal Auditors with respect to Competence Skills (Performance).

	COMP1	COMP2	COMP3	COMP4	COMP5
IA1	7,39	2,40	6,50	6,95	2,75
IA2	4,27	6,62	7,58	4,73	2,42
IA3	1,11	1,09	9,57	9,79	9,70
IA4	8,71	2,27	1,45	5,98	2,66
IA5	9,95	8,28	3,76	1,79	4,87
IA6	4,15	2,06	6,27	5,01	4,71
IA7	9,23	2,92	3,02	5,88	6,68
IA8	3,95	2,34	9,36	3,26	1,56
IA9	3,79	1,36	8,39	3,08	4,69
IA10	3,72	5,00	7,44	6,34	2,18

The weights for each criterion of Goal sub-factors, are 0.6 for GOAL1 and 0.4 for GOAL2. Regarding the competence sub-factor, each criterion is equally weighted (0.2 for the weight corresponding to COMP1,…,COMP5).

4.2Internal Auditor's Selection Results

The results of the model are shown and discussed in this section. Initially, for each internal auditor (IA1 – IA10), an overall score is calculated based on the weight representations as shown in Tables 2 – 11 and discussed in the Data sub-section. The results of the overall score as described in (1) are shown in Table 12. Since $0 \leq R_i^{OV} \leq 1$, each internal auditor is ranked on the descending order of values of R_i^{OV}.

Table 12: Overall scores for each Internal Auditor.

Internal Auditor	$\boldsymbol{R_i^{OV}}$
IA1	0.40
IA2	0.53
IA3	0.52
IA4	0.43
IA5	0.54
IA6	0.54
IA7	0.50
IA8	0.63
IA9	0.45
IA10	0.47

Therefore, the ranking is the IA8≻IA6≽IA5≻IA2≻IA3≻IA7≻IA10≻IA9≻IA4≻IA1 whereas, A≻B indicates that A is preferred to B.

4.3 Sensitivity analysis results

In order to examine the ranking of each internal auditor with respect to different weight representations, sensitivity analysis is performed. In many cases, it helps understand the range at which the solution is robust. By changing the weights on the top – level criteria, namely cognitive and behavioral, from 0 to 1 such that $w_{cogn,s=1}^{up} = 0.01$while $w_{beh,s=1}^{up} = 1 - w_{cogn,s=1}^{up} = 1 - 0.01 = 0.99$ then the ranking for all scenarios are shown in Figure 5.

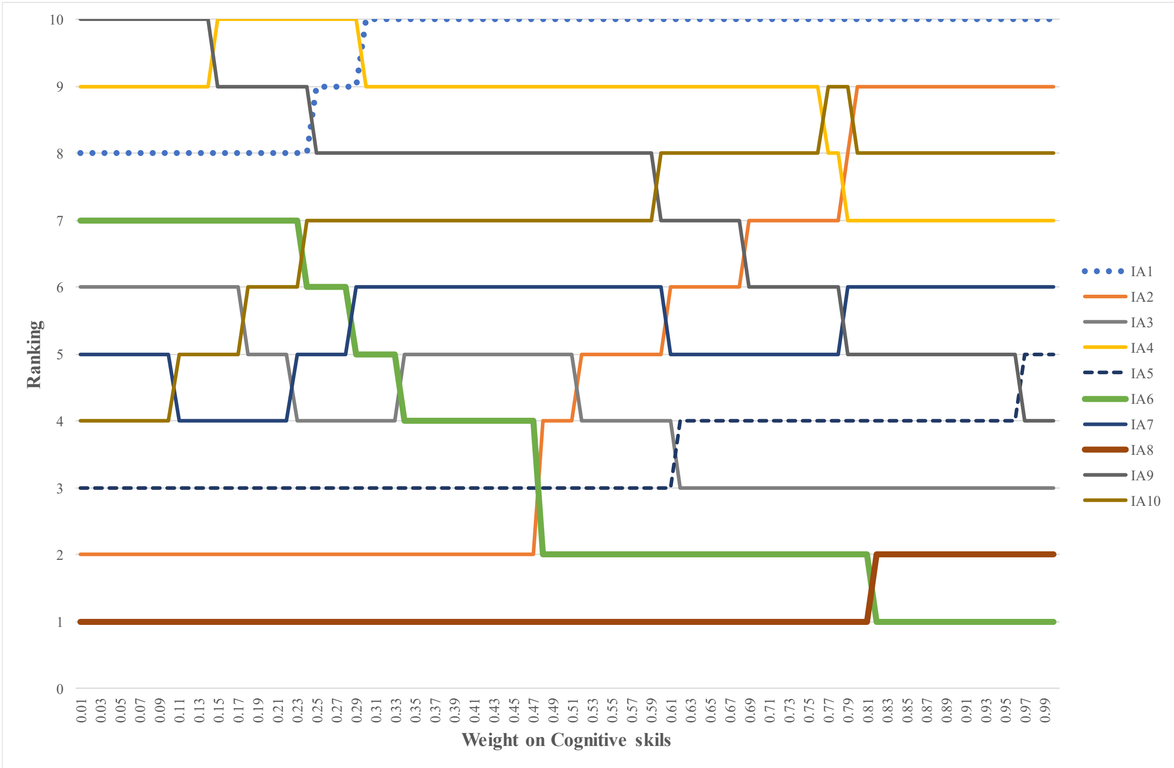


Figure 5: Sensitivity analysis of the ranking of each Internal Auditor.

From Figure 5, the sensitivity analysis of the ranking of each internal auditor can be seen. Each line corresponds to the ranking of each internal auditor with respect to changes of the weight on cognitive skill. Thus, for very low importance on cognitive skills which corresponds to high importance to behavioral skills since $w_{cogn}^{up} + w_{beh}^{up} = 1$, internal auditor 8 is ranked first while, for $w_{cogn}^{up} \geq 0.8$ internal auditor 6 is ranked 2nd. This analysis also identifies internal auditors that can potentially improve, like internal auditor 9 which is ranked as 6th for low values in the cognitive criterion (or larger values in the behavioral criterion) and is ranked as 3rd for high values in the cognitive criterion, and those who can potentially worsen their ranking, like internal auditor 1 which is ranked as 8th for low values in the cognitive criterion and for $w_{cogn}^{up} \geq 0.3$ is ranked as 10th.

4.4 Calculation of weights of top-level criteria with Non-Linear Programming

The interaction between hierarchical structures can provide valuable results. For example, in the proposed model two different scores have been calculated for the selection of Internal Auditors; one which is derived from cognitive and behavioral skills and the performance. Assuming that performance drives the selection of Internal Auditors based on cognitive and behavioral skills then the corresponding weights can be calculated based on the following Non-Linear Programming (NLP) model (3):

$$
\begin{aligned}
&\min d = \sqrt{\sum_{i=1}^{m} \left(R_i^{OV} - Perf_i\right)^2} \\
&s.t. \\
&R_i^{OV} = w_{cog} \cdot R_i^{COG} + w_{beh} \cdot R_i^{BEV} \\
&w_{cog} + w_{beh} = 1 \\
&w_{cog}, w_{beh} \geq 0
\end{aligned}
\qquad (3)
$$

The Non-Linear programming Model (3), is a specific form of Minkowski's distance for $\lambda = 2$ (Euclidean distance) as shown in the next formula.

$$L_\lambda(i) = \left(\sum_{j=1}^{m} \left| x_{ij} - a_j \right|^{\lambda} \right)^{1/\lambda}$$

Model (3) is Non-Linear due to the existence of Non-Linear terms (square root and power).Aim of the model is to minimize the distance (denoted with variable d) between the overall score as composed by behavioral and cognitive skills (R_i^{OV}) and performance overall score ($Perf_i$) for each internal auditor *i*. Assuming that the weights that correspond to cognitive and behavioral criteria are not fixed, minimizing the distance between the two overall scores (R_i^{OV} and $Perf_i$) the optimal values of the

NLP program will resemble that of the performance dimension. The technique is graphically illustrated in Figure 5.

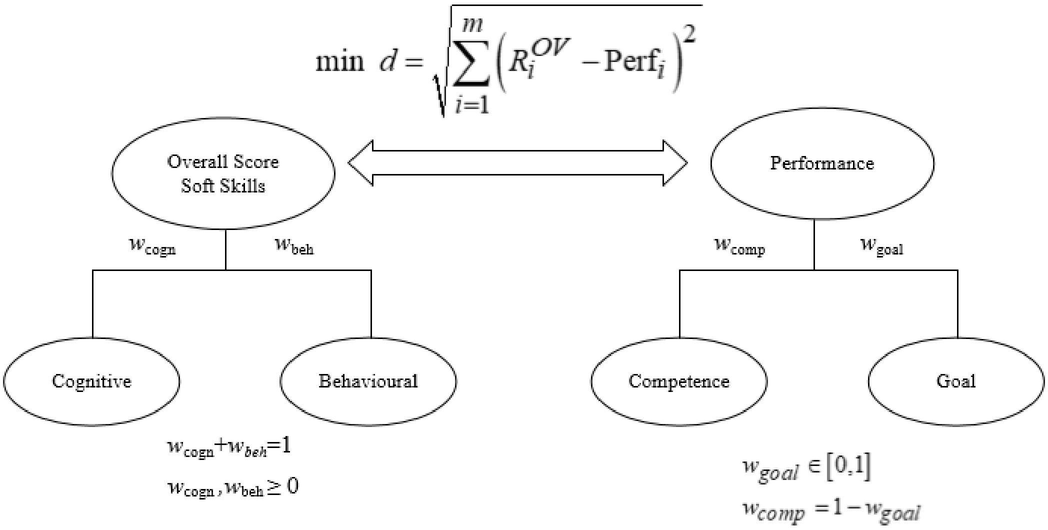


Figure 6: Graphical illustration of the NLP model

According to Figure 6by altering the weightage corresponding to goal and competence criteria respectively, then an overall score for performance is calculated. Solving NLP model (3) the optimal weights for cognitive and behavioral criteria are derived. The results of w_{cog} and $w_{beh}$are shown in Figure 6 for each scenario of w_{goal} and w_{comp}.

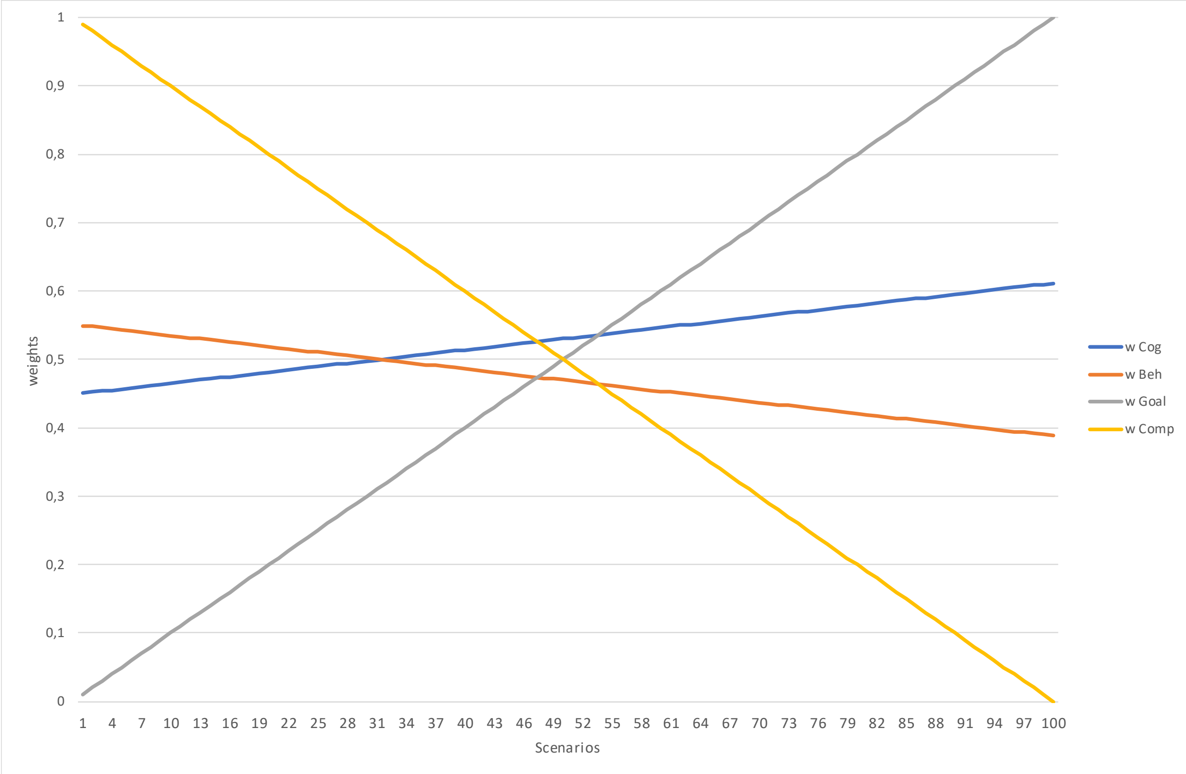


Figure 7: Robustness analysis of the weights derived from NLP model.

In Figure 7, the optimal weights, as derived from the NLP model measuring the overall score based on Cognitive and Behavioral and Performance models, are presented. In the NLP model (3), the TOPSIS model which ranks the internal auditors based on their performance is based on the scores of Tables 10 and 11. For each weight representation/scenario of $w_{goal} = 0.01, \ldots, 1$ with step 0.01 ($w_{comp} = 1 - w_{goal}$) composing 100 scenarios, NLP model (3) is solved and the optimal values of w_{cog}, w_{beh} are plotted in Figure 7 for each of the 100 scenarios.

From Figure 7, it can be seen that by covering the spectrum of weights from 0 to 1 (with w_{goal} and w_{comp}), the results on the w_{cogn} and w_{beh} seem to be quite robust, rendering values in the range of [0.45, 0.61] for the Cognitive and the range of [0.38, 0.55] for the Behavioral. The center of each interval is 0.53 and 0.46 respectively. The results enforce the initial assignment of weights to each sub-factor (0.5 for Cognitive and 0.5 for Behavioral).

The ranking of the internal auditors for optimal values of w_{cogn} and w_{beh} derived from NLP model (3), are shown in Figure8. It can be seen that IA8 is ranked 2[nd] for $w_{cogn} \in [0{,}45,\ 0.48]$ and is ranked 1[st] for $w_{cogn} > 0.48$.

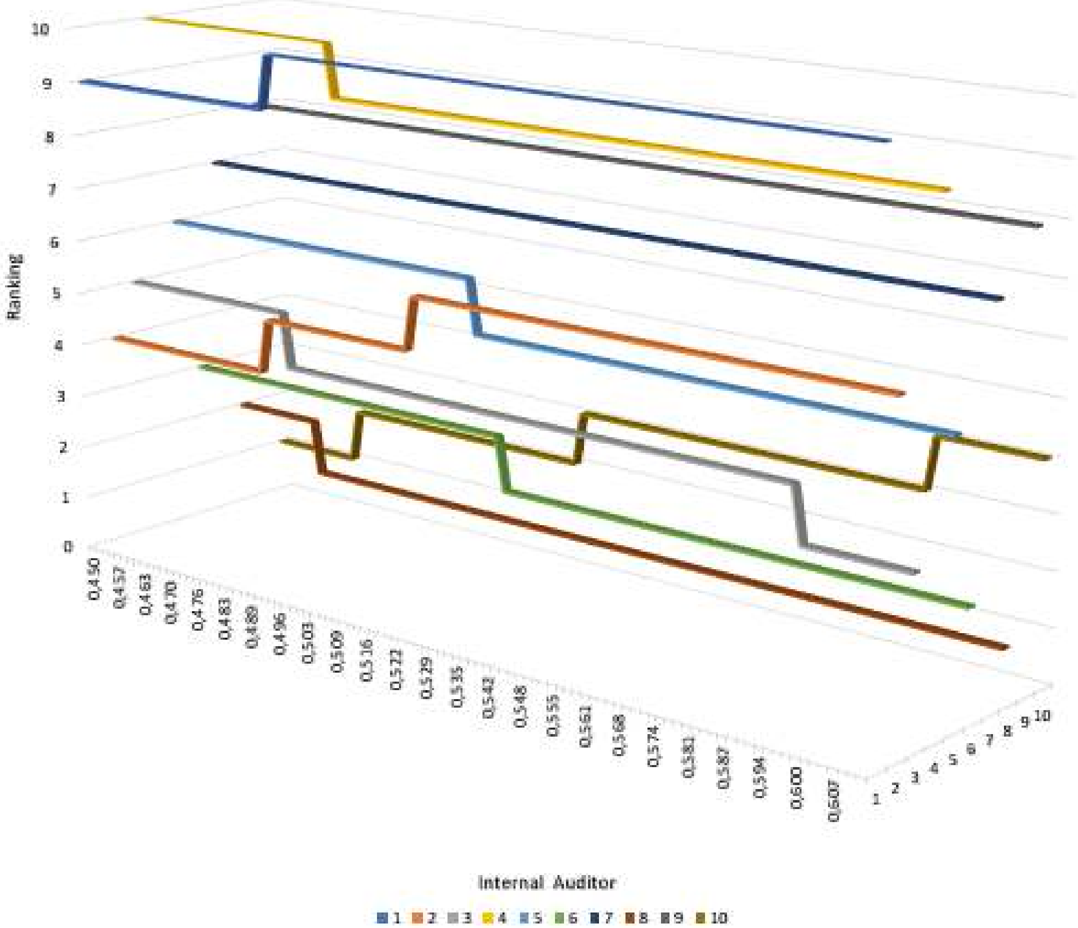


Figure 8: Ranking of internal auditors for $w_{cogn}{}^{*}(1 - w_{beh}{}^{*})$.

4.5 Calculation of weights of bottom level criteria with Linear Programming

Having calculated the weights of the top level criteria, the next step is to calculate the weights of the bottom level criteria. Since the weights of the top-level criteria have been derived from NLP model (3), then in order to determine the weights of the bottom level criteria the following LP model (4) is formulated:

$$\min d' = \sum_{i=1}^{m} \left(R_i^{OV,*} - \left\{w_{cog}{}^{*} \cdot R_i^{COG} + w_{beh}{}^{*} \cdot R_i^{BEH}\right\}\right) \tag{4}$$

$s.t.$

$R_i^{COG} = w_{tech} \cdot tech(i) + w_{analytic} \cdot analytic(i) + w_{appr} \cdot appr(i)$

$R_i^{BEV} = w_{pers} \cdot pers(i) + w_{intpers} \cdot intpers(i) + w_{org} \cdot org(i)$

$w_{tech} + w_{analytic} + w_{appr} = 1$

$w_{pers} + w_{intpers} + w_{org} = 1$

$w_{tech}, w_{analytic}, w_{appr}, w_{pers}, w_{intpers}, w_{org} \geq 0$

$R_i^{COG}, R_i^{BEV} \geq 0$

In LP formulation (4), the optimal weights as derived from NLP model (3) are denoted with $R_i^{OV,*}$ and aim of the model is to minimize the difference with the weighted scores R_i^{COG} and R_i^{BEV}. Solving LP model (3) the weights of the bottom level criteria are obtained:

- $w_{tech} = 0.4$, $w_{analytic} = 0.4$, $w_{appr} = 0.2$
- $w_{pers} = 0.2$, $w_{intpers} = 0.45$, $w_{org} = 0.35$

The advantage of this extension lies on the fact that the weights on one structure are objectively assigned based on another structure, therefore a comparison can be made in the end between the weights that were initially assigned and the calculated ones.

5. Conclusions

One of the most important departments of business nowadays is that of Internal Audit. This department provides services that relate to several subjects of the company, among which, the investigation of the correctness of the operations conducted among all departments. In most of the cases, an internal auditor may not have to do complex calculations of data, but needs to have a selection of skills which cannot be easily quantified. Therefore, the problem of selecting the right candidate for an internal audit position is not an easy task.

In this paper, TOPSIS technique was employed to calculate an overall score based on which each internal auditor will be finally ranked. The scores on each factor and sub factor, for Internal Auditor selection, were derived based on a real-life application from the HR department of a multi-national company in Greece. The weights have been calculated using AHP technique. The proposed model can identify successfully the ranking of internal auditors. Also, by examining scenarios on weights, different rankings are derived. For example, an internal auditor that is ranked 6^{th} with a specific combination of weights in cognitive and behavioral skills is ranked as 2^{nd} if the importance on the aforementioned skills is altered.

To investigate the robustness of the proposed solution, an NLP model is solved in order to compare the weights of the overall score between two TOPSIS models. More specifically, the weights proposed in performance, also derived by TOPSIS, were used to calculate the weights on cognitive and behavioral skills. Results show that the initial assignment of weights on cognitive and behavioral skills is close to the results from the NLP model which were derived through optimization. The model is extended to bottom level criteria using a LP model using fixed values from the NLP model which minimizes the distance between the two structures. From the LP model which was solved to determine the optimal values for weights of the bottom level criteria, it is concluded that the technical and analytic criteria share equal importance whereas the weight on the appreciative criterion is 20%. From the behavioral skills, the interpersonal criterion has the highest importance whereas the personal criterion has the lowest importance.

The proposed model can be applied in any type of personnel selection problem and can provide valuable insight by examining scenarios on the weights on each criterion (top or bottom level). One of the characteristics of the proposed framework is the determination of non-employable, quasi-employable and employable internal auditors by altering the weights on each criterion. Future directions entail the use of simulation or two stage process techniques based on the criteria examined.

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