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Faculty of Business Economics

Master of Management

Master's thesis

Analyzing Company Attractiveness with Multi-Criteria Methods

Azuka Peter Isaac

Thesis presented in fulfillment of the requirements for the degree of Master of Management, specialization Business Process Management

SUPERVISOR :

Prof. dr. Koenraad VANHOOF

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Abstract

Doing business today goes beyond meeting the required set profit target. Companies are constantly facing stiff competitions due technology advancement and innovations, and every organisation keeps striving to maintain leadership position in the sector. Businesses are now driven by technology which has made organisations to keep strategizing and devising best practices to attract not only their customers but also their employees who are the driving force behind their end products. In attracting existing and future employees, organisations will have to consider and choose factors that attracts good and loyal employees. However, to do this, they are faced with decision-making choices from many alternatives to choose from which makes it difficult for decision-makers to make effective and efficient decision since they have to rank them in order of preference. Thus, for companies to be competitive they will have to pay attention to those variables that increase their attractiveness to current and future employees. Thus, in this research the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) was adopted to rank the factors in order of preference which are considered attractive by employees.

Keywords: BPM, MCDM, TOPSIS, Rankings, Mean.

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1.0 Introduction

1.1 Introduction

The competitive nature of businesses in the twenty first century has led to new discoveries, inventions, as well as new innovations. The technology age has become a driver of businesses creating disruption in every sector, leading to stiff competition among organisations. Hence, every organisation keeps strategizing, and improving on business processes and decisions that will keep the company competitive and at par with other competitors. Thus, many decision-makers strives to improve their decision-making methods to align with the goal of the organisation.

Every organisation aspires to be not only competitive but also attractive. The ability of organisations to attract new, dedicated, and focused employees assign them in advantageous positions. However, organisations are faced with decision making dilemma ranging from choosing the best employee of the year to the most efficient production processes that yields the best profit by reducing the cost and identifying the most significant variables that are most competitive in the market. Decision making has always been a tough task for decision makers who are confronted with multiple alternatives to choose from and each decision leads to either a positive or negative result.

Over the years, several multi-criteria decision methodologies have been proposed by researchers and practitioners in order to support organisations to deal with the problem of decision making in every sector and areas of applications. This is due to the fact decision-makers need to improve their decision-making methods in order to compete effectively and also deliver value for customers.

A well-known and widely used MCDM method that relies on pairwise comparisons derived from experts' judgements to prioritize the observed alternatives is the Analytic Hierarchy Process (AHP) (Saaty, 2008); The basic idea of Elimination and Choice Translating Reality (ELECTRE) is to identify and eliminate alternatives, which are dominated (Vahdani, Mousavi, Tavakkoli-Moghaddam, & Hashemi, 2013). The ELECTRE method which was first introduced by Roy in the late 1960s, formulates concordance and discordance indexes in order to obtain outranking relationships, then renders a set of preferred alternatives by forming kernel (Yoon & Hwang, 1995). Also, Vahdani et al (2013), stated that this method can be utilized when a set of alternatives should be evaluated and selected with respect to a set of conflicting criteria by reflecting the decision-makers preferences(Vahdani et al., 2013).

Moreover, Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is a practical and useful technique for ranking and selection of a number of externally determined alternatives through distance measures (Shih, Shyur, & Lee, 2007), to mention a few. Furthermore, instead of normal average values, using TOPSIS as a ranking method can overcome the problem with ties that are of concern when considering only the average values to rank data (Rafiaani et al., 2017).

TOPSIS approaches both in literature as well as in practice and has provided practitioners with extensive methodological support in decision making. It has proved its usefulness in the real world to practitioners while researchers are constantly improving and extending the method in order to meet new challenges been faced by decision-makers. This method is based on a concept of identifying the positive ideal alternative that obtains the best level for all considered attributes/criteria, while the negative ideal alternative is indicated as the worst candidate of the underlying criteria More precisely, the ideal solution is the alternative that maximizes the benefit criteria and minimizes the cost criteria. On the contrary, the negative-ideal solution reduces the benefit criteria, and increases the cost criteria (Barros & Wanke, 2015). This method is able to identify an optimal method for making decision by minimizing costs and maximizing benefits for organisations.

Although the ranking index of TOPSIS is reasonable, it contains a flaw. That is, the ranking index is irrespective of the weights of separations of an alternative from the PIS and the NIS. In other words, no matter what weights the decision-maker assigns to these two separations, the ranking results would not differ as if he has no preference for these two separations (Kuo, 2017). The inability of the TOPSIS to give preferences to the ranking indexes is a set-back because decision makes will also like to know by how much are the separations different. Hence, due to this disadvantage of TOPSIS, there exist a gap and a modification should be done to take into account all alternatives simultaneously regarding the distances to both PIS and NIS (Rafiaani et al., 2017).

However, to solve this problem, a modified TOPSIS was proposed that will methodically take into account the separation measures. Dikopoulou et al (2015), suggested a Multi-Criteria Decision Method (MCDM), the Modified-Technique for Order Preference by Similarity to Ideal Solution (Modified-TOPSIS) (Dikopoulou, Napoles, Papageorgiou, & Vanhoof, 2015). The purpose of this research is to carry out a quantitative analysis in decision modelling using TOPSIS, with closer attention on the Modified-Technique for Order Preference by Similarity to Ideal Solution (Modified-TOPSIS).

1.2 Problem Statement

Research Questions (What do we want to know?)

The purpose of this research is to investigate which factors (variables) correlating to job attractiveness are the most important according to employee's preferences. For this reason, a technique of the MCDM family is applied in order to identify the significant factors that affect more the decisions of employees when they apply for a job.

Furthermore, MCDM's are studied in this research, which are the TOPSIS and Modified-TOPSIS. The basic assumption of the conventional TOPSIS is that there are *m*-alternatives (options) and *n*-attributes/criteria. For this reason, the dimension of the initial matrix is m*n, which each cell of the matrix signifies the score of each option with respect to each criterion. Since in our research, there are no criteria, we applied the modified TOPSIS (Dikopoulou et al., 2015) in order to identify not only the order of the observed variables (alternatives) but also the distances between them.

The optimal usage of Modified-TOPSIS and how it efficiently ranks decision alternatives is then perused. For an MCDM method that is intended to find a compromised solution, how to balance the separations of an alternative from the PIS and the NIS plays a crucial role and it is a major concern in realistic decision-making (Kuo, 2017).

In analysing company attractiveness with multi-criteria methods, this research thesis answers two main research questions from different perspectives. The first research question is aim at answering business wise question, while the second research question is developed to answer questions on the technical result.

Research Question 1: Is there a difference between TOPSIS and Modified-TOPSIS?

This research question is established to analyse the relationship and differences between TOPSIS and Modified-TOPSIS. Thus, it is important for decision-makers to know the differences and the relationship that exist between the two methods. This is because every organisation faces different decision-making challenges as every business is unique and are in different business sectors. Hence, this research question is aimed at finding the differences between the two methods and to what extend do they differ.

Research Question 2: To what extend does the ranking of gender and country differ?

The aim of this research question is to investigate the differences between the ranking of the gender and the country using the Modified-TOPSIS method. This is important for organisations that operate in many countries as it helps them to understand the cultural differences in the various countries where their businesses are located. More so, it helps them to understand the gender difference within a country and between two or more countries. The ability of the decision-makers to carry out a country and gender analysis enables the top management team to understand the peculiarity of each country and gender, and to know what method to adopt.

Hence, we aim to investigate how the Modified-TOPSIS positively improves decision making choices of organisations. Also, it helps at validating the assumption that the Modified-TOPSIS is more effective when ranking decision variables than the average (arithmetic mean) as it considers relative distances of the PIS and NIS between the alternatives.

Relevant Concepts (What do we know in advance?)

To carry out this research, we relied mostly on existing literatures on multi-criteria decision methods, TOPSIS method and case studies.

Research Goal (Why do we want to know?)

Over the years, there is an increasing number of literature review on TOPSIS method proposed by Hwang and Yoon in 1981. It has proven to be an efficient ranking method due to its efficiency and simplicity. Hence, Dikopoulou et al (2015), suggested a Multi-Criteria Decision Method (MCDM), the Modified- Technique for Order Preference by Similarity to Ideal Solution (Modified-TOPSIS) (Dikopoulou et al., 2015) which has proven to be capable of closing gap. The aim is to present how the Modified-TOPSIS can be effectively used to aggregate the preferences of thousands decision makers (group decision making) in order to rank alternatives identifying the PIS and NIS between alternatives when there is a lack of criteria. Moreover, the proposed method is appropriate method to order the alternatives of partial and/or full rankings.

1.3 Structure of the Thesis

This chapter already covers what this thesis is all about, the research is divided into seven sections in the preceding paragraphs including our developed research questions.

In chapter Two, we shall examine the key concepts related to this research in details. This starts by outlining the definition of BPM, including the evolution of business process. Afterwards, decision model and notation, decision logic, decision logic and decision tables including hit policies are examined. Next, the description of MCDM are then examined along with the implementation of MCDM in DMN. Moreover, the results of modified-TOPSIS and the statistical tests are interpreted.

Chapter Three refers to the applied methodology of this research in order to rank and infer the most important factors that affect job satisfaction. Furthermore, the description of the methodology and the reasons why this methodology is more suitable in our data.

Chapter Four presents the statistical tests used in the analysis. A quick review of parametric and non-parametric tests was examined to have a better understanding. Also, we examined the Kendall’s test which was used to examine the correlation between the countries.

In chapter five, we discussed and described the dataset which was used for the analysis. We were able to describe the dataset, and how it was collected.

Chapter six presents the results and discussion of the analysis based on country and gender. Furthermore, a comparison between the results of Modified-TOPSIS and Mean (Average) will be performed in order to show that these two techniques are not significantly different; while, we obtain more information about the distances between alternatives when the modified-TOPSIS is applied. Also, the correlation between the countries will be examined to see what relationship exist between the countries.

Lastly, Chapter seven is the discussion about our findings during the research, answers to our research questions, and the limitations during the research. The research ends with the general conclusion and recommendations.

2.0 Literature Review

2.1 Business Process Management

The evolution of Business Process Management (BPM) has giving rise to the believe that management of processes is the key to achieving organisational goals and objectives. Managers and business executives sees BPM as a method and tool for aligning business processes to its goals and objectives, thus providing value added benefits for its customers.

The emergence of Business Process Management and Notation (BPMN) standard in 2003-2005 revolutionized Business Process Management (BPM). This is because in the previous years, in order to automate a business process, business requirements are either in text-based requirements documents which has to be given to programmers or in modelling tools embedded within a proprietary Business Process Management Suite (BPMS) (Silver, 2016).

Bruce Silver (2016), stated that the revolutionary of business process management either manual or automatic using a set of diagrams with precise meaning defined by an industry standard and not by a proprietary tool. This is because it was business-friendly, BPMN 1.x was rapidly adopted by both business and technical users. This standard united both practitioners of business process management and those of business rule management (Silver, 2016).

Process Management	2000 Pre-BPMN • Requirements text-based Or proprietary modelling embedded in automation Suit. • Developers implement requirements in proprietary execution language.	2005 BPMN 1.x+ BPEL * Standards-based. modelling. * Mapped to a different Execution language (Standard or proprietary).	2011 BPMN 2.0 * Standards-based modelling. * Execution and modelling use a common Language.
Decision Management	2013 Pre-DMN	2016 DMN 1.0/1.1	2018

Figure 2.1: Evolution toward model-driven business-empowered implementation. Adapted from Bruce Silver (2016).

In figure 2.1, the 'traditional business rules market represents the Pre-DMN phase, which emphasis text-based decision requirements which is given to programmers for implementation and interpretation.

Business Process Management (BPM) is a disciplined approach to identify, design, execute, document, measure, monitor, and control both automated and non-automated business processes to achieve consistent, targeted results aligned with an organisation's strategic goals. Business Process Management involves the deliberate, collaborative, and increasingly technology-aided definition, improvement, innovation, and management of end-to-end business processes that drive business results, create value, and enable an organisation to meet its business objectives with more agility. BPM enables an enterprise to align its business processes to its business strategy, leading to effective overall company performance through improvements of specific work activities either within a specific department, across the enterprise, or between organisations (Group, 2016).

Giving the growing interest and the rise of BPM, has given rise to various definitions and meaning of BPM by different groups not limited to researchers, consultants, analysts, and top executives as to what BPM actually means.

Business Process Management (BPM) is a discipline combining business and information Technology (IT) perspectives with the ultimate goal of improving an organization's business operations (vom Brocke, Mathiassen, & Rosemann, 2014). BPM sets out to increase the effectiveness and efficiency of an organization; it is a significant contributor to overall organizational performance and competitiveness and it has become an increasingly important enabling factor of organizational innovation and transformation. Hence, BPM goes beyond the initial, cost-centre focus (e.g., Lean, Six Sigma) to help managers identify new revenue opportunities and non-monetary value-creation options (e.g., trusted, sustainable, and flexible processes), (Vrom Brocke et.al, 2014).

According to Brocke and Mendeling (2018), BPM uses an integrated set of corporate capabilities, including strategic alignment, governance, methods, technology, people, and culture, to analyze, design, implement, continuously improve, and disruptively innovate organizational processes (vom Brocke & Mendling, 2018). Furthermore, Jyothi Salibindla (2017), defined Business Process Management as the complete set of end-to-end activities required to complete a transaction. These processes are a set of activities and transactions that an organization conducts on a regular basis in order to achieve an objective.

Brocke and Rosemann (2015), made us to understand that Business Process Management is dedicated to analyzing, designing, implementing, and continuously improving organizational processes, (Brocke & Rosemann, 2015). They argued that While early contributions were focusing on the (re-)design of single processes, contemporary research calls for a more holistic view on the management of organizational processes. To that end, business process management is understood as an integrated set of corporate capabilities related to strategic alignment, governance, methods, technology, people, and culture

2.1.1 BPM in Multi-Criteria Methods (MCM)

According to Jyothi Salibindla (2017), Business Process Management (BPM) became the defacto standard for automating and managing an organization's business processes. BPM also provides the opportunity to analyze the activities and Key Performance Indicators (KPIs) while suggesting process improvements via process re-engineering. While BPM deals with optimization of business process, MCM's on the other hand lends itself to ways and methods in making efficient decisions in businesses. Managers and executives are interested in efficient processes that will align with the business goals and objectives.

Jyothis Salibindla (2017), stated that Intelligent Business Process predicts the bottlenecks in the process instances and task allocations and then prescribes alternatives, while Intelligent Business Human Activities learns the human decisions for each process instance and predicts the human input.

Multi-Criteria Methods (MCM) are effective methods deployed by experts in making and choosing decisions that adds value to the business. However, there are various MCDM methods which managers can use in making effective and efficient decisions. Multi-Criteria Decision Methods are able to answer questions regarding what and which business process to adopt and some of which includes but not all Analytic Hierarchy Process (AHP), Elimination and Choice Translating Reality (ELECTRE), and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS).

2.2 Decision Model and Notation

Knut Hinkelmann (2015), stated that the decision model and notation is a new standard from Object Management Group (OMG) (Hinkelmann, 2015). According to Knut Hinkelmann (2015), the purpose of DMN is to provide constructs that are needed to model decision, so that organisational decision-making can readily be depicted in diagrams, accurately defined by business analysts and (optionally) automated (Hinkelmann, 2015). The primary goal of DMN is to provide common notation that is readily understandable by all business users, from the business analysts needing to create initial decision requirements and then more detailed decision models, to the technical developers responsible for automating the decisions in processes, and finally, to the business people who will manage and monitor those decisions (Vanhoof, 2017).

Wiemuth et al. (2017), argued that DMN is only designed for decisions and cannot be used to represent a workflow or other functionalities, no processes can be modelled (Wiemuth et al., 2017).

OMG (2016), also stated that it is possible to use DMN in other standards such as BPMN as decision task. In order to display the decision logic in models as appropriate. DMN is designed to be usable alongside the standard BPMN, but the link is not limited to BPMN.

According to Object Management Group (2016), Decision Model and Notation (DMN) is a notation for decision handling, decision representation as well as implementation. They argued that DMN can be used to model decisions and their requirements, likewise for decision automation. This can be divided into two distinct levels: Decision Requirement and the Decision Logic Level. In the ***Decision Requirement Level***, an initial value, the ***decision***, is determined from a number of input data. The input data consist of results from other decisions, output of other tasks, or input from devices or users. However, the underlying ***Decision Logic Level***, which describes the Decision Requirement Level in more detail, is made up of one or more knowledge models that relate to business rules or other models or formalisms.

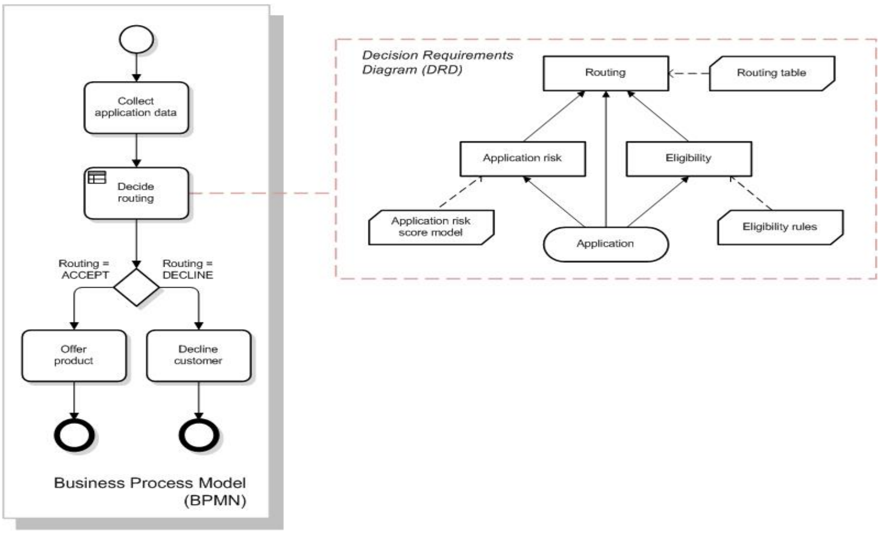


Figure 2.2 Business Process and Decision Models

2.2.1 Decision Logic

A business choice or selection, based on facts and knowledge, that ends or reduces uncertainty and results in an actionable value and outcome (Vanhoof, 2017).

A decision determines an output from a number of inputs by applying some decision logic. Decisions can be decomposed into sub-decisions, which are Top Decision Level which are viewed as selecting an answer from a range of possible answers. The Low Decision Levels often will simply provide input to other decisions (Hinkelmann, 2015).

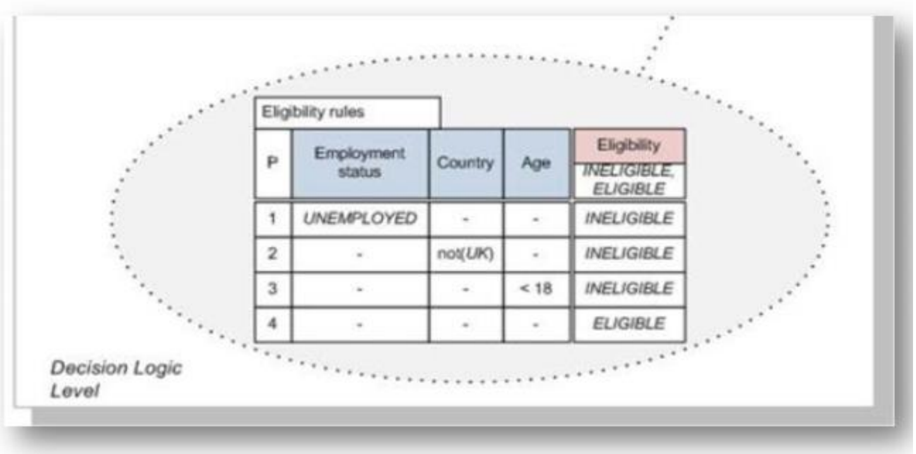


Figure 2.3 Decision Logic

However, the Object Management Group (2016), stated that the decision logic level of a decision model in **DMN** consists of one or more value expressions. The elements of decision logic modelled as value expressions include tabular expressions such as decision tables and invocations, and literal (text) expressions such as *age > 30*.

• A **literal expression** represents decision logic as text that describes how an output value is derived from its input values. The expression language may, but need not, be formal or executable: examples of literal expressions include a plain English description of the logic of a decision, a first order logic proposition, a Java computer program and a PMML document.

• A **decision table** is a tabular representation of decision logic, based on a discretization of the possible values of the inputs of a decision, and organized into rules that map discretized input values onto discrete output values.

• An **invocation** is a tabular representation of how decision logic that is represented by a business knowledge model is invoked by a decision, or by another business knowledge model. An invocation may also be represented as a literal expression, but usually the tabular representation will be more understandable. Hence, from a decision logic viewpoint, a decision is a piece of logic that defines how a given question is answered, based on the input data (Group, 2016).

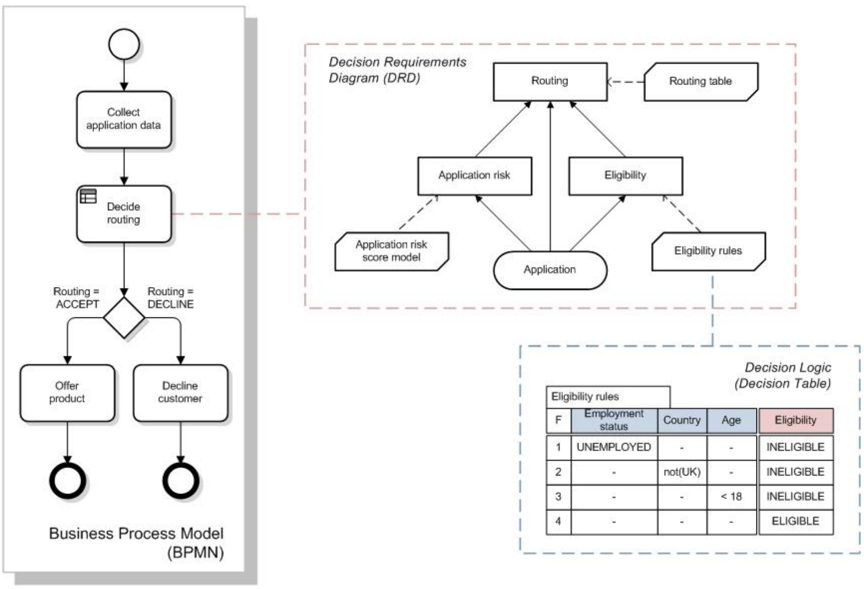


Figure 2.4 Business Process and Decision Models

Figure 2.4 gives us the overview of the integration of BPMN, Decision Logic and the Decision Requirements Diagram (DRD). A DRG models a domain of decision-making, showing the most important elements involved in it and the dependencies between them (Group, 2016). Figure 2.5 below gives the components, description, and notations of DRG.

Knut Hinkelmann (2015), stated that the Boxed Expression gives the notation for the decision logic which decomposes the decision logic into small pieces that are associated the elements of the Decision Requirement Diagram (DRD) (Hinkelmann, 2015).

Component		Description	Notation
Elements	Decision	A decision denotes the act of determining an output from a number of inputs, using decision logic which may reference one or more business knowledge models.	Decision
	Business Knowledge Model	A business knowledge model denotes a function encapsulating business knowledge, e.g. as business rules, a decision table, or an analytic model.	Business knowledge
	Input Data	An input data element denotes information used as an input by one or more decisions. When enclosed within a knowledge model, it denotes the parameters to the knowledge model.	Input data
	Knowledge Source	A knowledge source denotes an authority for a business knowledge model or decision.	Knowledge source
Requirements	Information Requirement	An information requirement denotes input data or a decision output being used as one of the inputs of a decision	
	Knowledge Requirement	A knowledge requirement denotes the invocation of a business knowledge model	
	Authority Requirement	An authority requirement denotes the dependence of a DRD element on another DRD element that acts as a source of guidance or knowledge	
Artifacts	Text Annotation	A Text Annotation consists of a square bracket followed by modeler-entered explanatory text or comment	Text annotation
	Association	An Association connector links a Text Annotation to the DRG Element it explains or comments on	

Figure 2.5: DRG Components.

2.2.2 Friendly Enough Expression Language (FEEL)

The Friendly Enough Expression Language (FEEL) is an expression language which is a script language for decision tables (Hinkelmann, 2015). Though not a programming language but it can reference variables to compute a value, but it cannot define variables (Silver, 2016). Furthermore, am important difference between FEEL and most other expression language is that FEEL element names may contain spaces, apostrophe, and other characters that are usually forbidden in element names (Silver, 2016). In line with this, the Object Management Group (2016), stated that in DMN, all decision logic is represented as boxed expressions. According to the Object Management Group (2016), the following are the features of FEEL;

- side-effect free,
- simple data model with numbers, dates, strings, lists, and contexts
- simple syntax designed for a wide audience
- Three-value logic (true, false, and null) based on SQL and PMML

According to the Object Management Group (2016), FEEL has two roles in DMN:

- As a textual notation in the boxes of boxed expressions such as decision tables
- As a slightly larger language to represent the logic of expressions and DRG's for the main purpose of composing the semantics in a simple and uniform way.

A graphical notation for decision logic is called Boxed Expressions. This notation serves to decompose the decision logic model into small pieces that can be associated with DRG artifacts. The DRG plus the boxed expressions form a complete, mostly graphical language that completely specifies Decision Models (OMG, 2016).

2.2.3 DECISION TABLE (DMN)

The Object Management Group (2016), defined a **decision table** as a tabular representation of decision logic, based on a discretization of the possible values of the inputs of a decision, and organized into rules that map discretized input values onto discrete output values. Ghala et al (2017), defined it as a table that contains the rules with their input and output, in addition to other technical details such as the hit policy and the completeness indicator (Ghlala, Kodia Aouina, & Ben Said, 2017). Basically, the outcome or output of the decision table is determined by the stated rules, input, and the hit policies made.

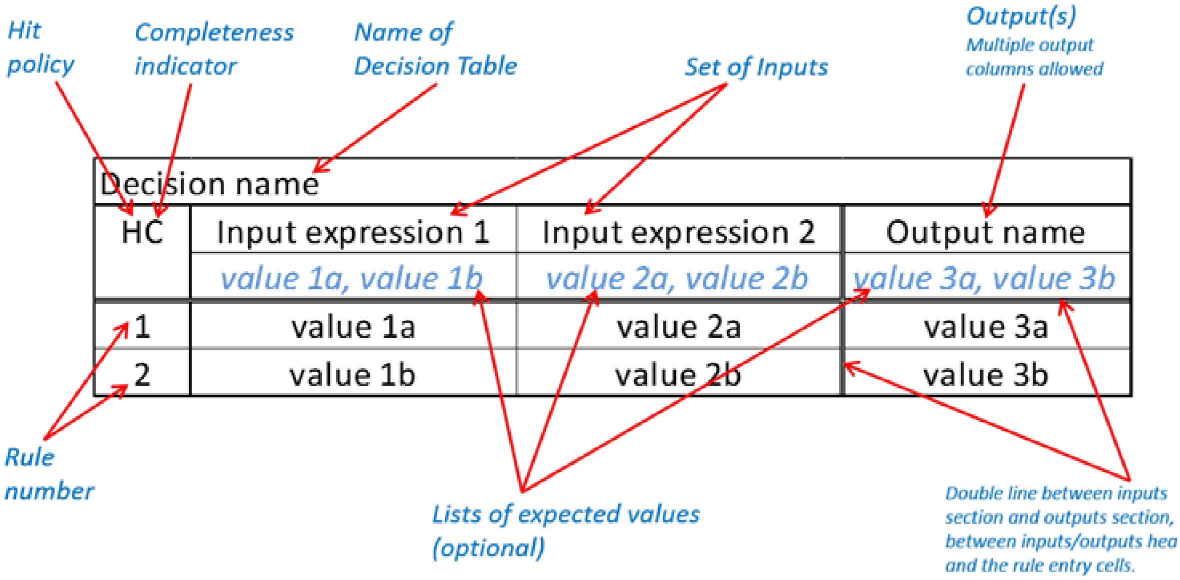


Table 2.1: Decision Table, proposed by Knut Hinkelmann (Hinkelmann, 2015).

Depending on size, a decision table can be presented horizontally (rules as rows), vertically (rules as columns), or crosstab (rules composed from two input dimensions). According to the Object Management Group (2016), the following rules applies:

1. In a horizontal table, all input columns SHALL be represented on the left of all output columns.
2. In a vertical table, all the input rows SHALL be represented above all output rows.
3. In a crosstab, all the output cells SHALL be in the bottom-right part of the table (Group, 2016). The number of decision problems a vital role regarding the size of a decision table as large and multiple decision difficulties will require a large decision table which will depend if it will be presented horizontally or vertically.

<u>**HIT POLICIES**</u>

A decision table normally has several rules. As a default, rules do not overlap. If rules overlap, meaning that more than one rule may match a given set of input values, the hit policy indicator is required in order to recognize the table type and unambiguously understand the decision logic. The hit policy can be used to check correctness at design-time. The hit policy specifies what the result of the decision table is in cases of overlapping rules, i.e. when more than one rule matches the input data. For clarity, the hit policy is summarized using a single character in a particular decision table cell. In horizontal tables this is the top-left cell and in vertical tables this is the bottom-left cell. The character is the initial letter of the defined hit policy Unique (U), Any (A), Priority (P), First (A), Collect (C), Output order (O) or Rule order (R). Crosstab tables are always Unique and need no indicator (Group, 2016).

HIT TABLES

According to Object Management Group (2016), a single hit table shall return the output of one rule only. That is, given all the input information's and hit policies, the table only returns one rule without preference. A multiple hit table may return the output of multiple rules (or a function of the outputs, e.g. sum of values). If rules are allowed to overlap, the hit policy indicates how overlapping rules have to be interpreted. Furthermore, they defined three types of hit tables available as follows:

1. **Single Hit Policy**: A single hit table may or may not contain overlapping rules but returns the output of one rule only. In case of overlapping rules, the hit policy indicates which of the matching rules to select. Some restrictions apply to tables with compound outputs. Single hit policies for single output decision tables are:

- **Unique**: no overlap is possible, and all rules are disjoint. Only a single rule can be matched. This is the default.
- **Any**: there may be overlap, but all of the matching rules show equal output entries for each output, so any match can be used. If the output entries are non-equal, the hit policy is incorrect, and the result is undefined.
- **Priority**: multiple rules can match, with different output entries. This policy returns the matching rule with the highest output priority. Output priorities are specified in the ordered list of output values, in decreasing order of priority. Note that priorities are independent from rule sequence.
- **First**: multiple (overlapping) rules can match, with different output entries. The first hit by rule order is returned (and evaluation can halt). This is still a common usage, because it resolves inconsistencies by forcing the first hit.

Also, OMG (2016), argued that hit tables are not considered good practice since they do not give a clear overview of the decision logic. It is important to distinguish this type of table from others because the meaning depends on the order of the rules.

2. **Multiple hit policies**: A multiple hit table may return output entries from multiple rules. The result will be a list of rule outputs or a simple function of the outputs. Multiple hit policies for single output decision tables can be:
    - **Output order**: returns all hits in decreasing output priority order. Output priorities are specified in the ordered list of output values in decreasing order of priority.
    - **Rule order**: returns all hits in rule order. Note: the meaning may depend on the sequence of the rules.
    - **Collect**: returns all hits in arbitrary order. An operator ('+', '<', '>', '#') can be added to apply a simple function to the outputs. If no operator is present, the result is the list of all the output entries.

    The following are the Collect Operators types;

    a) + (sum): the result of the decision table is the sum of all the distinct outputs.

    b) < (min): the result of the decision table is the smallest value of all the outputs.

    c) > (max): the result of the decision table is the largest value of all the outputs.

    d) # (count): the result of the decision table is the number of distinct outputs

2.3 Multi-Criteria Decision Methods (MCDM)

Since 1970s, Multi-Criteria Decision Making (MCDM) research has developed rapidly and has become a notably research topic due to complex practical decision problems that involve many and conflicting criteria as well as a considerable number of alternatives (Saaty & Ergu, 2015). Decision makers often face complicated decision problems with intangible and contrasting criteria. Numerous Multi-Criteria Making Decision (MCDM) methods have been proposed to handle the measurement of the priorities of conflicting tangible/intangible criteria and in turn use them to choose the best alternative for a decision (Saaty & Ergu, 2015). Managers and executives are often confronted with decision choices and every decision has an impact on the growth and development of the organisation. Thus, managers are often faced with hard choices knowing the impact of their choices will either benefit the organisation positively or negatively. Hence, they resort to use Multi-Criteria Decision Methods (MCDM) which are based on conflicting criteria's. This means that there is a conflict with the choice of method to use due to the numerous multi-criteria methods.

According to Ghlala et. al (2017), the decision making is more complicated if:

- A large number of possibilities to compare, it is combinatorial optimization.
- A significant number of decision makers thus, the recourse to social choice and the game theory.
- The consequences of actions are not safe, so we deal with decision criteria preference.
- Several criteria to be taken into consideration, therefore we are facing to Multiple Criteria Decision Making (MCDM).

Hence, decision-making in business process is generally confronted with the last situation of difficulty which is multi-criteria decision-making.

Over the years, some MCDM methods have been proposed by various authors. The most well-used are, the Analytic Hierarchy Process (AHP), the Elimination and Choice Translating Reality (ELECTRE), and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). However, many of the original MCDM methods have also been extended. The existence of these methods becomes a decision problem itself, and decision makers maybe uncertain about which one to use (Saaty & Ergu, 2015). That is to say deciding on which Multi-Criteria Method to be used becomes a difficult choice for managers.

Due to the modification of the existing MCDM methods, decision makers are faced with the appropriate method to apply to their decision problems. However, experts need to consider the peculiarity of their business requirements and the differences between each MCDM methods in order to acquire capable results. Each MCDM method has advantages and limitations. For this reason, every business manager (expert) is crucial to consider which method is suitable for each problem.

According to Yoon and Hwang (1995), Decision theories or methods have been categorized into normative or descriptive models depending on the way they are used.

- Normative Models: attempt to define the way a decision maker should make decision. Hence, these models are designed to assist people make optimal decisions. Practitioners of these types of models have their root in management science, statistics, and economics. Associated with these models are an array of axioms and guiding principles that a rational decision maker should purportedly follow when making decisions.
- Descriptive Models: attempt to describe the way that decision makers actually make decisions. These models are highly empirical and clinical in nature. Furthermore, many researchers have proven that decision makers do not always make rational cognitive decisions and that they will systematically violate axioms or principles set forth by normative models (Tversky & Kahneman, 1974, 1981). Proponents of these models have their background in the behavioural sciences, psychology, or marketing.
  (Yoon & Hwang, 1995).

Hwang and Yoon in 1981, classified a group of seventeen MCDM (or MADM) methods according to the type and salient features of information received from decision-makers. A modified taxonomy of thirteen methods is shown in figure 2.6 below. Given the level of information at the disposal of the managers, the MCDM method to be chosen becomes much easier for them, and this enables them to achieve the organisational goal.

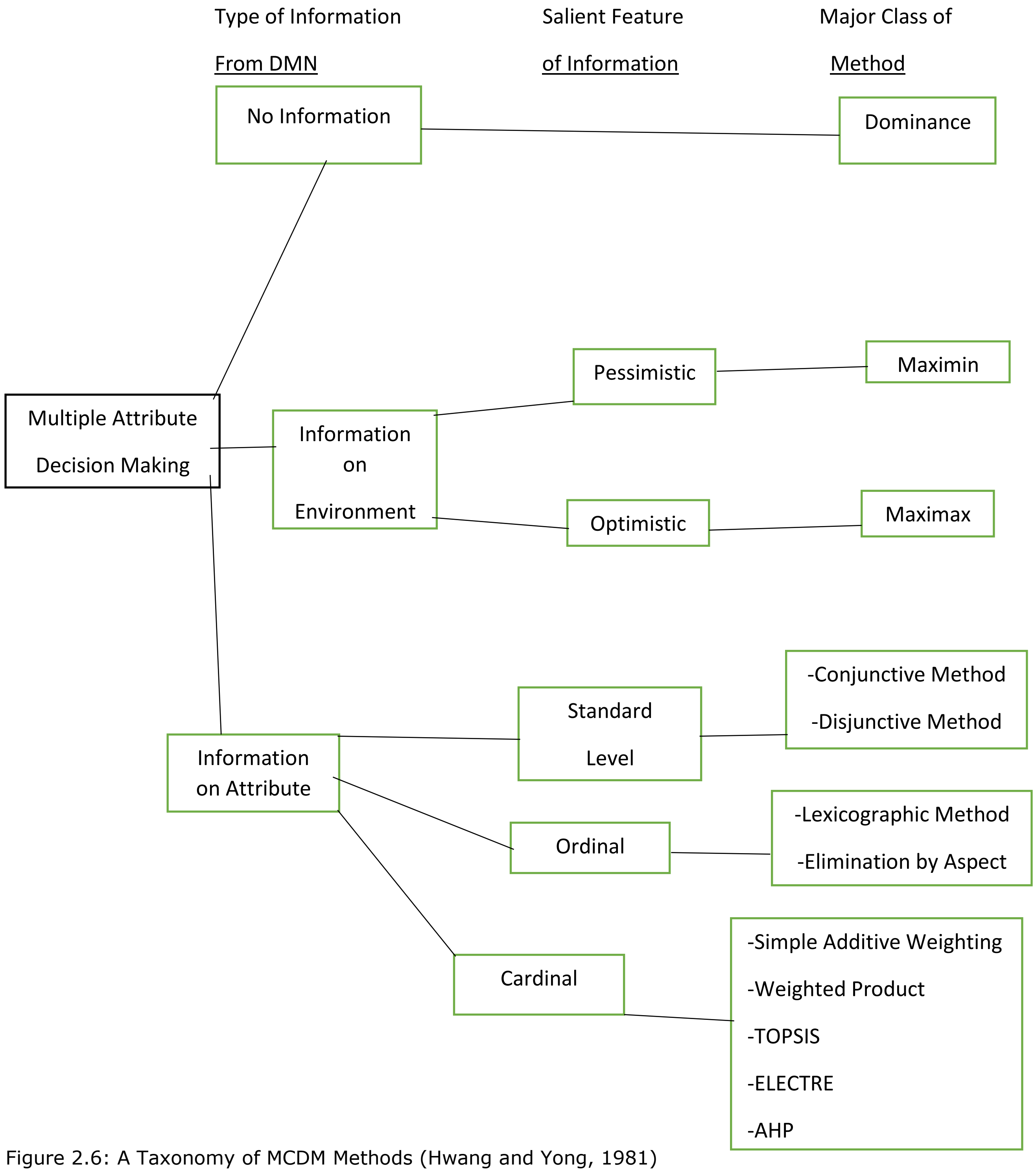


Figure 2.6: A Taxonomy of MCDM Methods (Hwang and Yong, 1981)

2.3.1 Multi-Criteria Methods in Business

A company's overall aspirations are comprised of a set of financial and non-financial goals. Managers striving for a firm's value creation face the challenge of aligning the conflicting goals of multiple stakeholders to maintain the firm's legitimacy to operate (Doś, 2017). Some of the organisational choices ranges from costs of production and manufacturing methods, to advertising strategies to adopt, customer relationship strategy, opening of new location, warehouse location, profit maximization strategy, portfolio selection and host of other challenges. The management executives and the business managers are also aware of the consequences of each choice through a cost-benefit analysis. Hence, they are left with a difficult task as to what MCDM method should be adopted in line with the strategy and goal of the business. For example, selecting appropriate ports of call for shipping lines is an important issue in ensuring the lines business continuity and the ports' (as well as their associated regional) economic growth (Gohomene et al., 2016).

Consequently, MCDM, is well-known branch of decision making. It evaluates and ranks a set of alternatives based on multiple conflicting criteria, and selects the best one with a trade-off mechanism (Lyu, Chow, Wang, & Lee, 2014).

2.3.2 Multi-Criteria Decision Methods with (MCDM) Decision Modelling (DMN)

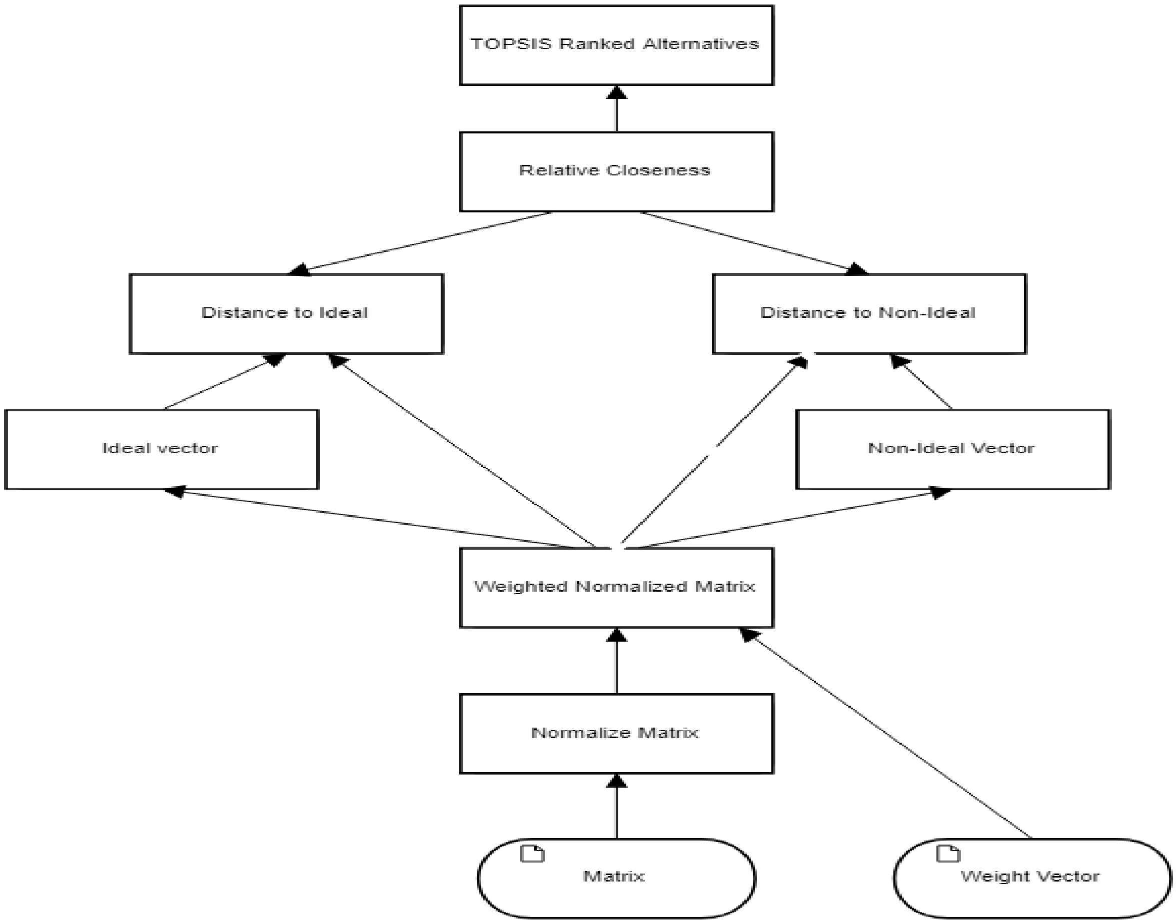
Decision making represents another field of investigation in order to improve the business process modelling. It was also an OMG centre of interest and has led to the invention of Decision Model and Notation (DMN) in 2013. We can classify decisions handled by the DMN in several categories such as eligibility, validation, calculation, risk, fraud, etc. Decision making by using DMN pushes towards defining roles and calls for specialization in construction of business processes. It also promotes agility and encourages the involvement of stakeholders in the project. The new model is a BPMN add-in (Ghlala et al., 2017).

Ghlala et al. (2017), stated that decision-making and its relationship to business processes showed a progression in dealing with decision. Indeed the first preoccupation was concentrated on the separation between decision-making modelling and process modelling (Ghlala et al., 2017). According to them, they believed that the first preoccupation of business managers is to make a distinct separation between what is decision-making modelling and process modelling as relates to the business.

However, Ghlala et al. (2017), were able to identify some short comings and limitations of the DMN relative to criteria preference (Ghlala et al., 2017). They highlighted the following limitations of DMN:

- Decision tables deals only with predefined decisions made from known criteria and it does not provide recourse to the concept of weight to handle business rules priority.
- Compliance levels, according to DMN specification, does not reach an automation level in the selection of a business rule from a proposed list, it is satisfied merely with its graphic representation.
- FEEL language, although it is extensible, does not discuss possible features like support of criteria preference.

However, these short comings can be resolved by using TOPSIS decision requirement diagram below, modelled in Trisotech. After the decision matrix has been created and normalised, weights are then assigned to the normalised matrix. The weights assigned makes it possible to measure the distances from the weighted normalised matrix to the PIS and NIS, hence, creating a preference criterion. Also, the distance between relative closeness and the ideal (non-ideal) vector can be measured by the distance to ideal (non-ideal) in the diagram below. The aim of the TOPSIS decision requirement diagram is to proffer solution to the third limitation of DMN heighted by Ghlala et al in 2017.



DMN's contribution in improving the decision-making in business process has become an established fact, but no evolution's wheel is never stopped. The focus is around upgrading DMN to cover likewise important aspects such has preference criteria. Making the DMN able to handle preference criteria can help decision-makers in situations where the choice is not obvious and automatic processing must be done to achieve a better result (Ghlala et al., 2017).

Multi-Criteria-Decision Model and Notation (MC-DMN) is a novel notation based on the standard DMN. It can be implemented to make the DMN able to cover preference criteria (Ghlala et al., 2017). This novel approach enables DMN to handle the problem of preference criteria which is a limitation of Decision Modelling. Thus, managers are able to rank their preferences and make better decisions.

2.3.3 Multi-Criteria Decision Methods (MCDM) with TOPSIS

In the current dynamic business environment, decision making process demands more refined and robust performance evaluation systems. Decision Maker (DM) evaluates several businesses alternatives, using various criteria before making the final decision. The specialty of Multi-Criteria Decision Methods (MCDM) tools in evaluating relative performance and setting appropriate benchmarks has helped the DM to rank various alternatives on the basis of various conflicting criteria measured in different units and to come up with the best decision. Also, these tools facilitate peer evaluation of an individual Decision Making Unit (DMU) in the sample of several DMUs (Chitnis & Vaidya, 2018).

MCDM tools such as TOPSIS have found its application as a standalone technique or as an integrated tool for effective decision making. In the literature review done by Behzadian et al. (2012) on TOPSIS, various applications of TOPSIS in different areas such as: Supply Chain Management and Logistics, Manufacturing Systems, Business and Marketing Management, Health, Safety and Environment Management, Human Resources Management, Energy Management, Chemical Engineering, Water Resources Management and other topics studied (Chitnis & Vaidya, 2018).

3.0 Ranking Methods

Various MCDM have been invented over the years which have greatly impacted on decision making positively. Different organisations use's different Multi-Criteria Decision Methods to rank multiple decisions according to the business need(s). The following methods will be reviewed: Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Modified-TOPSIS.

3.1 TOPSIS

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), was developed by Hwang and Yoon in 1981, it is a simple ranking method in conception and application (Ghlala et al., 2017). A MADM problem with *m*-alternatives that are evaluated by *n*-+attributes may be viewed as a geometric system with *m* points in the *n*-dimensional space. Hwang and Yoon (1981) developed the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) based on the concept that the chosen alternative should have the shortest distances from the positive ideal solution and the longest distance from the negative-ideal solution (Yoon & Hwang, 1995). The ranking method of TOPSIS, allows managers (experts) to rank their multiple decisions by inspecting the effects and impacts of each decision from the real or ideal objective of the organisational goal.

Furthermore, Hus-Shih Shih et al. (2007), defined TOPSIS as a practical and useful technique for ranking and selection of a number of externally determined alternatives through distance measures (Shih et al., 2007). Hence, the ranking method enables the managers show the distances and or differences of each choice of alternative from the goal they want to achieve, and the distances between the rank of each set of alternatives can also be determined. Thus, Shih et al. (2007), argued that it is not uncommon for certain groups to constantly make complex decisions within organizations. However, for using any MADM technique, e.g., TOPSIS, it is usually assumed that the decision information is provided in advance by a team or a task group. Thus, Shih et al., (2007), propose post-work to enhance TOPSIS as a problem-solving tool (Shih et al., 2007).

According to Barros & Wanke (2015), Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS) is a multi-criteria decision making technique, which similar to DEA (Data Envelopment Analysis), ranks a finite set of units based on the minimisation of distance from an ideal point, and the maximisation of distance from an anti-ideal point (Barros & Wanke, 2015). They deduced that TOPSIS method ranks a set of multiple attributes based on the maximum distance from no-ideal solution, and also ranks them based on the minimum distance from the ideal solution. More precisely, the ideal solution is the one that maximises benefit and also minimises total costs. On the contrary, the negative ideal solution is the one which minimises benefit, and also maximises cost. Thus, the maximization distance from the anti-ideal point is the longest distance from the ideal solution which is further away from the business goals and strategy, while the minimization distance from the ideal point gives attributes whose distances are close to the organisation goals and objectives.

3.1.1 Positive-Ideal Solution (PIS) and Negative-Ideal Solution (NIS)

Yoon & Hwang (1995), defined an ideal solution as a collection of idea levels (or ratings) in all attributes (Yoon & Hwang, 1995). However, they stated that the ideal solution is usually unattainable or infeasible. Then to be as close as possible to such an ideal solution is the rationale of human choice (Yoon & Hwang, 1995). Due to the multiple goals, strategies, and objectives of an organisation, it is assumed that organisations may not attain all their objectives but rather they can be close as possible to their goals and objectives. Since the ideal is dependent on the current limits and constraints of the economy and technology, a perceived ideal is utilized instead to implement the choice rationale in a normative decision process (Yoon & Hwang, 1995).

Shih et al (2007), stated that distance is the degree or amount of separation between two points, lines, surfaces, or objectives. Originally TOPSIS utilized Euclidean distances to measure the alternatives with their PIS and NIS so that the chosen alternative should have the shortest distance from the PIS and the farthest distance from the NIS. In fact, there are a couple of common distance measures, i.e., Minkowski's $L\ p$ metric in an n-dimensional space, where $p \geq 1$ (Shih et al., 2007).

Zhongliang Yue (2011), it simultaneously considers the distances to both positive ideal solution (PIS) and negative ideal solution (NIS), and a preference order is ranked according to their relative closeness, and a combination of these two distance measures. That is, the best alternative has simultaneously the shortest distance from the PIS and the farthest distance from the NIS. The PIS is identified with a ''hypothetical alternative'' that has the best values for all considered attributes whereas the NIS is identified with a ''hypothetical alternative'' that has the worst attribute values (Yue, 2011).

Yoon & Hwang (1995), denoted the positive-ideal solution as follows

$$\mathbf{A^+ = (x_1^+, \ldots\ldots\ldots, x_j^+, \ldots\ldots\ldots, x_n^+)} \qquad \mathbf{1}$$

Where X_j^* is the best value for the jth attribute among all available alternatives. The composite of all best attribute ratings attainable is the positive-ideal solution, whereas the negative-ideal solution is composed of all worst attribute ratings attainable. The negative-ideal solution is given as

$$\mathbf{A^- = (x_1^-, \ldots\ldots\ldots, x_j^-, \ldots\ldots\ldots, x_n^-)} \qquad \mathbf{2}$$

Where X_j^- is the worst value for the jth attribute among all available alternatives (Yoon & Hwang, 1995).

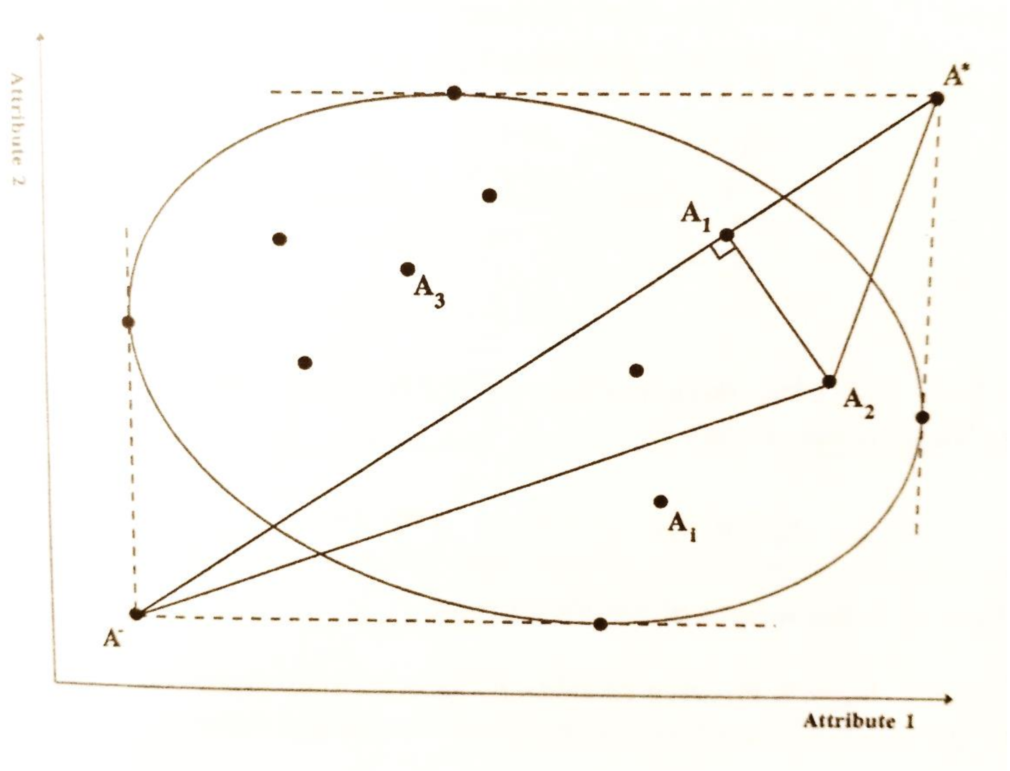


Figure 2.7: Euclidean Distances to PIS and NIS in Two-Dimensional Space(Yoon and Hwan, 1981).

Yoon & Hwang (1995), argued that the chosen alternative that is closest to the PIS does not always concur with the chosen alternative that is farthest from the NIS (Yoon & Hwang, 1995). In figure 2.7, they sighted an example by considering two alternatives $\mathbf{A_1}$ and $\mathbf{A_2}$ and concluded that $\mathbf{A_1}$ is the closest to $\mathbf{A^+}$ but $\mathbf{A_2}$ is the farthest from $\mathbf{A^-}$.

Over the years, TOPSIS method have proved its wide applications. TOPSIS method is the third most popular place takes the Business and Marketing Management (approximately 12.3% of all papers come under in this category) after Supply Chain Management, Logistics and Design, and Engineering and Manufacturing Systems which take the first and the second place, respectively (Dikopoulou et al., 2015).

TOPSIS has been successfully applied to solve selection/evaluation problems with a finite number of alternatives because it is intuitive and easy to understand and implement (Safari, Cruz-Machado, Zadeh Sarraf, & Maleki, 2014).

3.1.2 Steps in Performing TOPSIS

The steps below explain how TOPSIS can be applied:

Step 1. Create the decision matrix D by each decision maker. Develop an evaluation matrix consisting of m-alternatives and n-criteria, with the intersection of each alternative and criteria given as $\mathbf{X_{Ij}}$**.** In table 3.7 below, $\mathbf{a_i}$, indicates the alternatives up to the ith alternative, where i=1,…..,m.

CR_j gives the corresponding *jth* attribute where j-1,2,…..,n. Also, $\mathbf{X_{ij}}$ gives the performance of the *ith* alternatives, this alternative represents an integer. It is worth mentioning that CR_j can represent either cost or benefit. Benefit are represented by J^+, while costs are represented by J^-.

Alternatives	**Criteria**			
	CR 1	***CR 2***	**...**	***CR$_n$***
a$_1$	*x$_{11}$*	*x$_{11}$*	...	*x$_{11}$*
a$_2$	*x$_{21}$*	*x$_{22}$*	...	*x$_{21}$*
⁞	⁞	⁞	⁞	⁞
a$_m$	*x$_{m1}$*	*x$_{m2}$*	...	*x$_{mn}$*

Table 3.7: Decision Matrix D with M*N size

Step 2. Calculate Normalized Ratings: Normalize the decision matrix to transform the different attribute dimensions into non-dimensional attributes, which allows comparisons across the values of indicators and participants. The *R* indicates the square root of the additional element value squares, according to each indicator. The *R* is calculated for each participant *j* of the decision-making matrix.

For i =1, 2, ..., m and j = 1, 2, ..., n.

Then, divide each column by R_{ij} to get r_{ij}, which represents the elements of the new normalized decision-making matrix and are calculated as:

$$R_j = \sqrt{\sum_{i=1}^{m} x_{ij}^2} \qquad \textbf{4}$$

Divide each column by R_j to get r_{ij} which represents the elements of new normalised decision making. The vector normalization is performed first which is used to compute r_{ij}, which results in

$$r_{ij} = x_{ij} \Big/ \sqrt{\sum_{i=1}^{m} x_{ij}^2} \qquad \textbf{5}$$

Step 3: Calculate the Weighted Normalized Decision Matrix. This can be calculated by multiplying each column of the normalized decision matrix in step 2 with the coefficients $\mathbf{w}_j$, where j=1, ………, n, where

$$\sum_{j=1}^{n} w_j = 1$$

The weighted normalized is then calculated as

$$v_{ij} = w_j r_{ij} \qquad \textbf{6}$$

Where i=1,…….,m; j=1,……….n.

Step 4: Identify Positive-Ideal and Negative-Ideal Solutions. First, we identify the positive ideal solution, denoted as A^+, which is then calculated as:

$$A^{+} = \{(\max_{i} v_{ij} \mid j \in J_1), (\min_{i} v_{ij} \mid j \in J_2) \mid i = 1,2,..., m\} =$$

$$= \{v_1^{+}, v_2^{+},..., v_j^{+},..., v_n^{+}\} \qquad \textbf{7}$$

Next, we identify the negative ideal solution, denoted as A^-, and calculated as

$$A^{-} = \{(\min_{i} v_{ij} \mid j \in J_1), (\max_{i} v_{ij} \mid j \in J_2) \mid i = 1,2,..., m\} =$$

$$= \{v_1^{-}, v_2^{-},..., v_j^{-},..., v_n^{-}\} \qquad \textbf{8}$$

Step 5: Calculate the Separation Measures. The separation measure is the Euclidean distance of each alternatives. The separation of each alternative from the positive-ideal solution A^+ is given as:

$$S_i^{+} = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^{+})^2} \quad , \text{ i=1,....,m} \qquad \textbf{9}$$

Also, the separation of each alternative from the negative-ideal solution A^- is given as:

$$S_i^{-} = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^{-})^2} \quad , \text{ i=1,......,m} \qquad \textbf{10}$$

Step 6: **Calculate the Relative Closeness to the Ideal Solution**. Here the relative closeness C_i is calculated as follows:

$$C_i = \frac{S_i^{-}}{S_i^{+} + S_i^{-}}; 0 \le C_i \le 1; i = 1,..., n \qquad \textbf{11}$$

When C_i=0, then $0 \le C_i \le 1$, then $a_i = A^-$, which is the negative ideal point and

when C_i=1, then $a_i = A^+$, which is the positive ideal point.

Step 7: **Rank the order of the preferences**. After completion of step 6, we choose an alternative with the maximum C_i.

3.2 MODIFIED-TOPSIS (M-TOPSIS)

Dikopoulou et al (2015), suggested the Modified- Technique for Order Preference by Similarity to Ideal Solution (Modified-TOPSIS) (Dikopoulou et al., 2015). The ideal and non-ideal solutions are determined by using a normalized matrix. Next, the Euclidean indicator distances from the PIS and NIS points are calculated and the relative closeness to the PIS is obtained, which is in the range of zero to one. The main difference between the modified-TOPSIS and the conventional TOPSIS is observed in the initial decision matrix. Specifically, the modified TOPSIS, contains *m* alternatives (options) and *n* participants which each value indicates the performance rating of alternative A_i with respect to participant P_j; while, TOPSIS uses *m* alternatives (options) and *n* attributes/criteria and obtain as input the score of each option with respect to each criterion(Dikopoulou et al., 2015).

Moreover, TOPSIS was modified to handle the partial rankings, in other words, the zero values in the initial matrix developed for the calculation process of TOPSIS (Dikopoulou et al., 2015). The modification was done in order to take into account all indicators simultaneously regarding the distances to both PIS and NIS, which in the present study correspond respectively to the "most relevant indicator" and "least relevant indicator", determined by the correspondent's in study. However, the ideal and non-ideal solutions are determined by using a normalized matrix.

3.2.1 Steps to Perform the MODIFIED-TOPSIS

Because every impact category in this survey corresponds to different indicators,

The following steps below illustrates how the Modified-Technique for Order Preference by Similarity to Ideal Solution (Modified-TOPSIS) was used in analysing the dataset.

Step 1: Each decision maker created a decision matrix D. Next, we develop an evaluation matrix consisting of *m*-alternatives and *n*-participants**.** In table 3.8 below, $\mathbf{A_i}$, indicates companies attractiveness impact indicator, where i=1,…..,m; Pj signifies the jth correspondents in the study, j= 1,2,….., n. xij represents the performance of the ith alternative as regards to the jth participant, which correspond to an integer in the range 0–5.

Alternatives	Criteria			
			………	
	P_1	P_2		P_n
A_1	x_{11}	x_{11}	……….	x_{11}
A_2	x_{21}	x_{22}	……….	x_{21}
⁞	⁞	⁞	⁞	⁞
A_m	x_{m1}	x_{m2}	…	x_{mn}

Table 3.8: Decision Matrix D with M*N size

Step 2: **Calculate Normalized Ratings:** Normalize the decision matrix to transform the different attribute dimensions into non-dimensional attributes, which allows comparisons across the values of indicators and participants. The *R* indicates the square root of the additional element value squares, according to each indicator. The *R* is calculated for each participant *j* of the decision-making matrix.

For i =1, 2, ..., m and j = 1, 2, ..., n.

Then, divide each column by R_{ij} to get r_{ij}, which represents the elements of the new normalized

decision-making matrix and are calculated as:

$$R_j = \sqrt{\sum_{i=1}^{m} x_{ij}^2} \qquad \mathbf{12}$$

Divide each column by R_j to get r_{ij} which represents the elements of new normalised decision making. The vector normalization is performed first which is used to compute r_{ij}, which results in

$$r_{ij} = x_{ij} \Big/ \sqrt{\sum_{i=1}^{m} x_{ij}^2} \qquad \mathbf{13}$$

Step 3: Calculate the Weighted Normalized Decision Matrix. This can be calculated by multiplying each column of the normalized decision matrix in step 2 with the coefficients $\mathbf{w}_j$, where j=1, ………, n. The importance of every impact category is not equal due to the different values that are given by the participants; therefore, the assigned impact category' values are aggregated, and the average values are normalized. Such that

$$\sum_{j=1}^{n} w_j = 1$$

The weighted normalized is then calculated as

$$v_{ij} = w_j r_{ij} \qquad \textbf{14}$$

Where i=1,…….,m; j=1,……….n.

Step 4: Identify Positive-Ideal and Negative-Ideal Solutions. First, we identify the positive ideal solution, denoted as A^+, which is then calculated as:

$$\begin{aligned} A^+ &= \{(\max_i v_{ij} \mid j \in J_1), (\min_i v_{ij} \mid j \in J_2) \mid i = 1,2,..., m\} = \\ &= \{v_1^+, v_2^+, ..., v_j^+, ..., v_n^+\} \end{aligned} \qquad \textbf{15}$$

Next, we identify the negative ideal solution, denoted as A^-, and calculated as

$$\begin{aligned} A^- &= \{(\min_i v_{ij} \mid j \in J_1), (\max_i v_{ij} \mid j \in J_2) \mid i = 1,2,..., m\} = \\ &= \{v_1^-, v_2^-, ..., v_j^-, ..., v_n^-\} \end{aligned} \qquad \textbf{16}$$

Step 5: Calculate the Euclidean Distance. The separation measure is the Euclidean distance of each alternatives. The separation of each alternative from the positive-ideal solution A^+ is given as:

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2} \text{ , i=1,….,m} \qquad \textbf{17}$$

Also, the separation of each alternative from the negative-ideal solution A^- is given as:

$$S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2} \text{ , i=1,……,m} \qquad \textbf{18}$$

Step 6: **Calculate the Relative Closeness to the Ideal Solution**. Here the relative closeness C_i is calculated as follows:

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-}; 0 \le C_i \le 1; i = 1,..., n \qquad \textbf{19}$$

When C_i=0, then $0 \le C_i \le 1$, then $a_i = A^-$, which is the negative ideal point and

when C_i=1, then $a_i = A^+$, which is the positive ideal point.

Step 7: **Rank the order of the preferences**. After completing step 6, we ranked the indicators according to C_i and selected the maximum C_i which is the most relevant indicator.

4.0 Statistical Tests

Statistical tests are confirmatory tests because they are used to confirm results of analysis done. In statistics, statistical tests used can either be parametric or non-parametric. The two tests will further be examined.

4.1 Parametric Tests

A parametric test can be used as a confirmatory test to confirm result of an analysis. Parametric data has an underlying normal distribution such that the variable in question, when plotted, demonstrates a predictable and symmetrical bell-shaped graph, a so-called Gaussian distribution. The principal advantage of data of this type is that since the shape of its distribution is known, inferences may be drawn about values that lie within any part of the distribution curve (Grech & Calleja, 2018).

Lisbeth Bruckers (2004), listed some characteristics of parametric tests, which are

- Assumptions about the distribution in the population is known
- Conditions are often not tested
- Test depends on the validity of the assumptions.
- It is the most powerful test if all assumptions are met.

(Bruckers, 2004).

4.2 Non-Parametric Tests

A non-parametric test (sometimes called a distribution free test) does not assume anything about the underlying distribution (for example, that the data comes from a normal distribution). That's compared to parametric test, which makes assumptions about a population's parameters (for example, the mean or standard deviation); When the word "non-parametric" is used in stats, it doesn't quite mean that you know nothing about the population. It usually means that you know the population data does not have a normal distribution (Stephanie, 2014).

Non-parametric tests are distribution-free and make less, if any, assumptions about the distribution of the data's pattern. Non-parametric tests do not make use of the distribution of the data involved and little or no assumptions which makes it difficult to tell know the pattern of the data. They instead use the rank order of individual measurements in the dataset rather than the measurements themselves (Grech & Calleja, 2018).

Non-parametric tests are often the alternative test to use when the sample size is small. Using non-parametric tests in large studies may provide answers to the wrong question, thus confusing readers (Fagerland, 2012). The usefulness of non-parametric tests as alternatives to t-tests for non-normally distributed data is most pronounced for small studies (Fagerland, 2012). Grech and Calleja (2018), stated that non-parametric tests have conventionally been advocated for smaller datasets and/or non-normally distributed data. However, there has been a progressive relaxation of these restrictions (Grech & Calleja, 2018). Examples of Non-parametric tests include but not all Friedman test, Mann-Whitney test, Kruskal-Wallis test, Kendall's Tau (T). Further review on Kendall's tau (T) will be considered below.

Lisbeth Bruckers (2004), summarizes the characteristics of nonparametric tests as follows:

- Fewer assumptions about the distribution in the population (e.g. continuity)
- In case of small sample sizes often the only alternative (unless the nature of the population distribution is known exactly)
- Less sensitive for measurement error (uses ranks).
- Can be used for data which are inherently in ranks, even for data measured in a nominal scale.
- Easier to learn.

(Bruckers, 2004).

Table 4.1 below summarizes the properties of parametric and non-parametric tests.

Properties	Parametric Tests	Non-Parametric Tests
Distribution	Assumed to be Gaussian (normal)	Any
Variance	Assumed to be homogeneous	Any
Typical data	Discrete or continuous interval	Ordinal or Nominal
Dataset relationship	Independent	Any
Central measurement	Mean	Median

Table 4.1: Adapted from Grech & Calleja (2018)

4.2.1 Kendall's Tau (T)

Kendall's Tau is a non-parametric measure of relationships between columns of ranked data (Stephanie, 2016). The Tau correlation coefficient returns a value of -1 to 1, where

- 0 means no relationship
- 1 is a perfect relationship.
- -1 indicates negative relationship

Guidelines for interpretation of a correlation coefficient

Correlation coefficient		Association
-0.3 < r < 0.3		Weak
-0.5 to -0.3	or 0.3 to 0.5	Moderate
-0.9 to -0.5	or 0.5 to 0.9	Strong
-1 to -0.9	or 0.9 to 1	Very Strong

Table 4.2: Correlation range

The Kendall (Kendall, 1955) rank correlation coefficient evaluates the degree of similarity between two sets of ranks given to a same set of objects. This coefficient depends upon the number of inversions of pairs of objects which would be needed to transform one rank order into the other (Abdi, 2007). The Kendall's rank coefficient is vastly used in showing the relationship between ranks or variables, it determines the degree of relationship between the ranks. Furthermore, In order to do so, each rank order is represented by the set of all pairs of objects (e.g., [a,b] and [b, a] are the two pairs representing the objects a and b), and a value of 1 or 0 is assigned to this pair when its order corresponds or does not correspond to the way these two objects were ordered. However, this methodology gives a set of binary values which can be used to compute the Person correlation coefficient (Abdi, 2007).

Abdi (2007), stated that the Kendall coefficient of correlation can be obtained by normalizing the symmetric difference such that it will take values between −1 and +1 with −1 corresponding to the largest possible distance (obtained when one order is the exact reverse of the other order) and +1 corresponding to the smallest possible distance (equal to 0, obtained when both orders are identical) (Abdi, 2007).

Maurice Schaeffer (1956), opined that the Kendall's tau (τ) should be used to reflect the growing realization among psychologists of the inadequacy of the Pearson product-moment coefficient (r) in a number of circumstances like When the variates to be correlated show sharp departures from normality or When the variates to be correlated are unmeasurable according to an objective scale, as in the case of ratings or preferences of judges, or when precise measurement is impractical and the raw data must be sets of ranks (Schaeffer & Levitt, 1956).

The advantages of the Kendall's correlation coefficient have over the Pearson's correlation coefficient when it involves data with ranks or preferences is the reason why we used the Kendall's Tau (T) correlation in our analysis to evaluate the relationship between the ranks in Average and Modified-TOPSIS.

Tau (τ) is defined as

$$T = S/(n(n-1)/2) \qquad \textbf{3}$$

n= is the number of items ranked

S= (X-Y).

X= Objects in the same order, that is the number of item pairs whose ranking orders agree. Sometimes called concordant pairs.

Y= Objects in different order, that is the number of item pairs whose ranking orders disagree. They are also referred as discordant pairs.

Hence, the Kendall’s Tau correlation will be used in this research study.

5.0 Data Description

Research is simply the process of finding solutions to a problem after a thorough study and analysis of the situational factors (Sekaran & Bougie, 2016). We can simply remark that research is an activity which involves solving a problem after examining the problem at hand. Research can be undertaken for two different purposes. One is to solve a current problem faced by the manager in the work setting, demanding a timely solution. For example, a particular product may not be selling well, and the manager might want to find the reasons for this in order to take corrective action, this called Applied Research. The other is to generate a body of knowledge by trying to comprehend how certain problems that occur in organizations can be solved, which is called Basic, or fundamental or pure research (Sekaran & Bougie, 2016).

Furthermore, Sekaran et al (2016), identified eight hallmarks of a scientific which are rigour, testability, replicability, precision and confidence, objectivity, generalisability, parsimony, and purposiveness (Sekaran & Bougie, 2016)

5.1 Research design

Based on the purpose of the study, which is to investigate the causal–effect relationships of the effects of decision-making (ranking) methods on company's attractiveness, a positivism approach to research is adopted. In addition, the quantitative research approach is chosen.

Element	**Type**
Research Approach	Positivism
Design Method	Qualitative
Purpose of research	Causal
Unit of analysis	Individuals

Table 5.1: Research design table

5.1.1 Data collection

The data of our research question was obtained from Prof. Koen Vanhoof (Hasselt University) which consist of a case study carried out by a doctoral student. The data used for this research was collected from twenty-three (23) different countries covering the following contents: Asia, Australia, Europe, North America and South America. The table below summarizes the number of countries in each continent.

Australia	Asia	Europe	South America	North America
2	5	13	1	2

Table 5.2: Distribution of data

5.1.2 Description of dataset

The dataset was explored to get an insight into the variables, as well as missing values. The table below gives the name and description of variables in the dataset. Five variables were identified in the dataset which are sector, activity, age, study, and gender.

The sector variable is divided into twenty-three categories which describes various business sectors. The activity variable describes the job position of employees, their roles as well as their level in that organisation which is divided into six categories while the gender category describes the describes the sex of individuals in the organisation which is classified into male and female. More so, the age variable which describes the working age of the employees was classified into three. Lastly, the study variable tells us the level of education of the employees which was further divided into seven categories. These categories reveal the level of education attained by the employees.

Variable	**Description**
Sector	Describes the sector and or industry an employee works (1,2,3,…….,23)

Activity	Describes the level, role, and position of employees (1,2,3,4,5,6)
Age	Gives the age of employees (1,2,3)
Study	Indicates the level of education (1,2,3,4,5,6,7)
Gender	Describes gender category (1,2)

Table 5.3: Variable descriptions

Participants were asked to rank the 17 variables corresponding to job satisfaction (Table 5.4).

Variable Notation	Interpretation
VV1	Financially healthy
VV2	Offers good training
VV3	Offers long-term job security
VV4	Offers international/global career opportunities
VV5	Offers career progression opportunities
VV6	Has strong management
VV7	Offers interesting job content
VV8	Has a pleasant working atmosphere
VV9	Offers competitive salary & employee benefit
VV10	Ensures a good work-life balance
VV11	Is conveniently located
VV12	Has a strong image/strong values
VV13	Offers quality products/services
VV14	Concerned with environment & society (CSR)
VV15	Uses latest technologies (innovative)
VV16	Offers flexible working arrangement (flexitime, teleworking, etc.)
VV17	Promotes diversity in the workplace (age, gender, race)

Table 5.4: Notation for variables

Furthermore, participants were grouped by gender (male and female), Sector, Age, Activity, and Study (Education).

Activity: 1.00= 'Production Worker' 2.00= 'Office Worker' 3.00= 'First-level manager/supervisor' 4.00= 'Middle-level manager/branch manager' 5.00= 'Top-level manager/board member' 6.00= 'Other'	Study-Education: 1.00= 'No Diploma' 2.00= 'Primary Education' 3.00= 'Secondary Education' 4.00= 'Further Education (no university)' 5.00= 'University' 6.00= 'Post University' 7.00= 'Other'
Age: 1.00= '18-24 years' 2.00= '25-44 years' 3.00= '45-65 years'	Gender: 1.00= 'Male' 2.00= 'Female'

Table 5.5: Dummy variables

Variable Notation	Interpretation
S1	Agriculture, forestry, fishing
S2	Automotive
S3	Construction
S4	Finance (Banking & Insurance)
S5	FMCG
S6	Human Resource
S7	Industrial/Manufacturing
S8	Informatics/Consulting
S9	Consulting

S10	Mining
S11	Non-Profit (Healthcare/NGO/Public services)
S12	Public administration (government)
S13	Education
S14	Pharmaceutical/Chemical
S15	Power/Utilities/Telecom
S16	Real Estate or rental and leasing
S17	Retail trade
S18	Wholesale trade
S19	Services (business services/Cleaning/Media/Entertainment/Recreation)
S20	Media
S21	Transport/Logistics/Warehousing
S22	Travel/Leisure/Hospitality
S23	Other

Table 5.6: Variables in the Sector

6.0 Results and Discussion of Analysis

6.1 Exploratory Data Analysis

There are twenty-three (23) countries in this study with seventeen (17) variables (V1 to V17) which were ranked based on country and gender. The table below report the number of correspondents/subjects in each country. Luxembourg obtain the lowest number of respondents with 680 people while Netherlands has the highest number of respondents with 10.026 individuals.

No	Country Name	Number of Correspondents	No	Country Name	No of candidate
1	France (NEW)	9151	13	Singapore	5893
2	France	9151	14	Canada	5929
3	Netherlands	10026	15	United States	6768
4	Germany	6097	16	Argentina	6327
5	Poland	6476	17	Hong Kong	6827
6	Spain	7183	18	China	7727
7	United Kingdom	7242	19	Switzerland	4329
8	Italy	5601	20	Hungary	4842
9	Australia	7060	21	Sweden	6185
10	New Zealand	4201	22	Russia	6740
11	India	6477	23	Luxembourg	680
12	Japan	5840			

Table 6.1: Summary of participants by country

6.2 Ranking by Countries

The datasets were further explored by performing country analysis on the seventeen (17) variables. The ranking of the seventeen variables based on country showed some little differences between the average (mean) and the Modified-TOPSIS. The result from tables 6.2 to 6.6 gives the best top 5 ranked variables for each of the 23 countries, and the result showed that there are some differences and similarities in the ranking of the variables among the 23 countries.

Table 6.2 to 6.6 gives us the ranking of the best five variables in each of the twenty-three countries was observed that in Hungary, Australia, Canada, and New Zealand, that variable 9 (V9) which is 'offers competitive salary and employee benefit' has been ranked first. Variables 3 (V3) which is 'offers long-term job security' and 10 (V10) which is 'ensures a good work-life balance where ranked second and third respectively. However, variable 8 (V8) which implies 'has a pleasant working atmosphere was ranked fourth while variable 7 (V7) which is 'offers interesting job content' was ranked fifth. It is worthy to note that the order in which these variables were ranked in these countries implies that priority is given to variable 9 (V9) followed by V3, V10, V8, and V7 in that order.

Also, from tables 6.2 to table 6.6, we observed that variable nine (V9) has also been ranked first in other eighteen countries making it a total of eighteen countries ranking V9 first in the twenty-three countries representing 78%. The ranking of variable nine as the first ranked variable among others explains the attractiveness of companies to employees and the society at large. Job applicants are strongly attracted to companies that offers a competitive salary as well as other company benefits (such as meal vouchers, company cars, health insurance, train ticket re-imbursement) which other companies are not offering or cannot offer. Examples of such companies includes Google, Microsoft Corporation, Goldman Sachs, Price Water Coop, Deloitte to mention a few. However, companies who are not able to provide such offers tend to lose their best employees and also find it difficult to attract new ones.

Lee et al (2014), stated that when employees sense their salary is lower than the market average, they will have unsatisfactory feelings, make less effort to the organization and feel tired or want to leave the job (Lee & Lin, 2014). Companies who can offer both competitive salary and benefits uses this as a competitive advantage in attracting highly qualified employees and experts.

Furthermore, variable three (V3) which means "offers long-term job security" was not only ranked second by these countries but was also ranked second by other eight countries (Spain, France, Belgium, Argentina, UK, USA, India, and Poland) making it a total of twelve countries ranking V3 as second most ranked variable which represents 52% of the whole countries.

When employees perceive that there is no job security in an organisation, they are generally not motivated or attracted to such organisations because they might be laid off after few months or years of joining the organisation. Employees are more interested working for a long term and building a career rather than changing jobs year. Hence, they are more attracted to organisations who can provide them job security, companies where they can work on a term, build career without been afraid of being out of job after joining the organisation for a few months.

From the ranking, variable 10 (V10) which is 'ensures a good work-life balance' was ranked third. Employee's generally are attracted to organisations who can provide them a good work-life balance, by helping them to balance work and their personal life. More so, V10, was ranked third by Switzerland, Hong Kong, and USA making it a total of seven countries ranking V10 on the third position representing 30.4%. variable 8 (V8) was ranked fourth by these countries and by other six countries (France, Hong Kong, USA, Singapore, Italy, and Poland) making it ten countries which ranked V8 as fourth most attracting variable to consider by employees which represents.

However, variable 7 (V7) which represents 'offers interesting job content' was ranked fifth by these countries and others such as Spain, Argentina, Canada, and Poland, making it countries that ranked V7 fifth. Employees and potential employees enjoy doing what they like best and not been forced to do what is out of their interest. Employees doing jobs not in their best interest ends up with poor performance, which will also affect the total output of the organisational.

Rank	**Switzerland**		**Australia**		**Spain**		**Luxembourg**		**Russia**	
Best Five Ranking	M-TOPSIS	Mean	M-TOPSIS	Mean	M-TOPSIS	Mean	M-TOPSIS	Mean	M-TOPSIS	Mean
1	V8	V8	V9	V9	V9	V9	V3	V3	V9	V9
2	V9	V9	V3	V3	V3	V3	V9	V9	V1	V1
3	V10	V10	V10	V10	V5	V5	V8	V8	V7	V7
4	V3	V3	V8	V8	V10	V10	V7	V7	V3	V3
5	V16	V16	V7	V7	V7	V7	V10	V10	V5	V5

Table 6.2: Ranking by countries

Rank	**Sweden**		**Hungary**		**China**		**France**		**Hong Kong**	
	M-TOPSIS	Mean	M-TOPSIS	Mean	M-TOPSIS	Mean	M-TOPSIS	Mean	M-TOPSIS	Mean
1	V7	V7	V9	V9	V9	V9	V9	V9	V9	V9
2	V8	V8	V3	V3	V5	V5	V3	V3	V5	V5
3	V9	V9	V10	V10	V3	V3	V7	V8	V10	V10
4	V3	V3	V8	V8	V1	V10	V8	V7	V8	V8
5	V11	V11	V7	V7	V10	V1	V10	V10	V1	V1

Table 6.3: Ranking by countries

Rank	**Argentina**		**USA**		**Canada**		**Singapore**		**Japan**	
	M-TOPSIS	Mean	M-TOPSIS	Mean	M-TOPSIS	Mean	M-TOPSIS	Mean	M-TOPSIS	Mean
1	V9	V9	V9	V9	V9	V9	V9	V9	V9	V9
2	V3	V3	V3	V3	V3	V3	V10	V10	V7	V7
3	V8	V8	V10	V10	V8	V8	V3	V3	V8	V8
4	V5	V5	V8	V8	V10	V10	V8	V8	V3	V3
5	V7	V16	V1	V1	V7	V7	V5	V5	V11	V11

Table 6.4: Ranking by countries.

Rank	**India**		**New Zealand**		**Italy**		**UK**		**Poland**	
	M-TOPSIS	Mean	M-TOPSIS	Mean	M-TOPSIS	Mean	M-TOPSIS	Mean	M-TOPSIS	Mean
1	V9	V9	V9	V9	V3	V3	V9	V9	V9	V9
2	V3	V3	V3	V3	V9	V9	V3	V3	V3	V3

3	V1	V1	V10	V8	V1	V8	V7	V8	V1	V8
4	V10	V10	V8	V10	V8	V1	V10	V10	V8	V1
5	V5	V5	V7	V7	V10	V10	V8	V7	V7	V7

Table 6.5: Ranking by countries

Rank	Germany		Netherlands		Belgium	
	M-TOPSIS	Mean	M-TOPSIS	Mean	M-TOPSIS	Mean
1	V3	V3	V9	V9	V9	V9
2	V9	V9	V8	V8	V3	V3
3	V8	V8	V3	V3	V8	V8
4	V10	V10	V7	V10	V7	V7
5	V1	V1	V10	V7	V10	V10

Table 6.6: Ranking by countries

Rank	Variable	Number	Percentage
1	V9	18	78.26
2	V3	3	13.04
3	V8	1	4.35
4	V7	1	4.35
Total		23	100

Table 6.7: Percentage distribution of variable

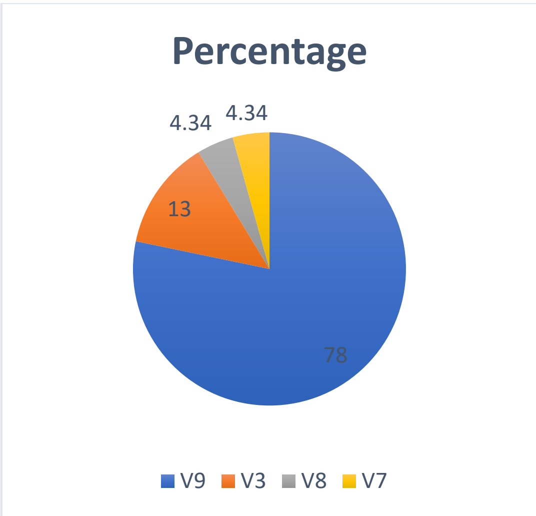


Figure 6.1: percentage of variables

6.3 Ranking by Gender

To broaden our view, a gender by country analysis was carried out in the twenty-three countries for comparisons. The values in table 6.9 to 6.13 gives an insight about the top five ranked variables using Modified-TOPSIS method based on gender in each of the twenty-three countries. We compare the rankings between both genders in Switzerland and found out there are some slight differences between the genders. It was observed that variable 9 was ranked best in the male category while among the female variable 8 was ranked best

Rank	Switzerland		Australia		Spain		Luxembourg		Russia	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
1	V9	V8	V9	V9	V9	V9	V9	V3	V9	V9
2	V8	V9	V3	V3	V3	V3	V3	V9	V1	V1
3	V10	V10	V10	V10	V5	V10	V7	V8	V7	V7
4	V3	V3	V8	V8	V7	V5	V8	V7	V3	V3
5	V16	V16	V7	V7	V10	V7	V10	V10	V5	V5

Table 6.9: Ranking by genders

Rank	Sweden		Hungary		China		France		Hong Kong	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
1	V7	V7	V9	V9	V9	V9	V9	V9	V9	V9
2	V9	V8	V3	V3	V5	V5	V3	V3	V5	V10
3	V8	V9	V10	V10	V3	V3	V7	V8	V10	V8
4	V3	V3	V8	V8	V1	V1	V8	V7	V3	V1
5	V11	V11	V7	V7	V10	V10	V5	V10	V1	V5

Table 6.10: Ranking by genders

MALE

Ranking of the variables by the male gender showed that 20 countries representing 86.9% ranked variable 9 (V9) has the best variable to consider in terms of company attractiveness. While 2 countries representing 8.7% ranked variable 3 (V3) as the best variable to consider, one country which is Sweden representing 4.35% ranked variable 7 (V7) as the best variable of consideration.

Furthermore, there are some variabilities in the ranking of the least variable by the male gender across the countries. We observed that 10 countries ranked variable 17 as the least variable of attractiveness representing 43.5%, while 9 countries ranked variable 14 representing 39.1% as the least variable. Also, 3 countries ranked variable 15 which is 13% as the least ranked and 1 country (Argentina) ranked variable 6 which is 4.3% as the least ranked variable.

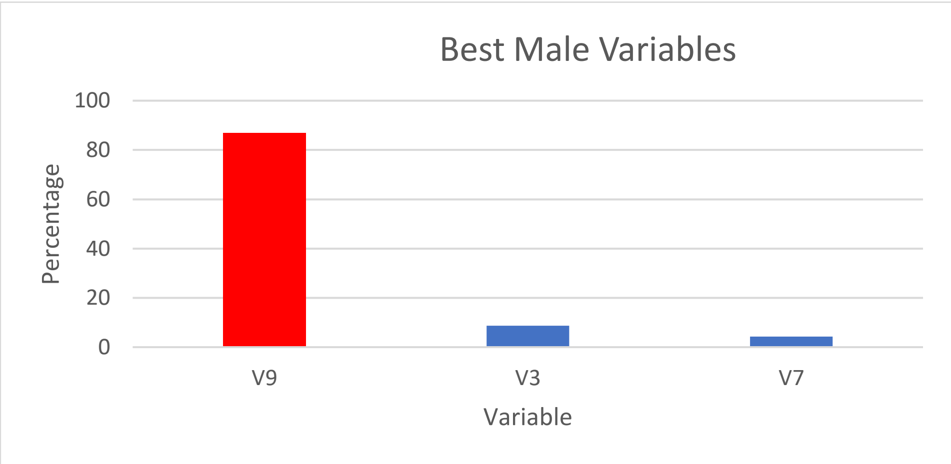


Figure 6.2: Variable ranking by male gender

FEMALE

Ranking of variables by the female gender in table 6.11 to 6.13 showed that 17 countries which is 73.9% ranked variable 9 as the most important variable that attracts employees and the society at large, while 3 countries representing 13% ranked variable 3 (V3) as the best ranked variable among the females. Also, 2 countries representing 8.7% ranked variable 8 (V8) as best variable, and only 1 country which is 4.3% ranked variable 7 (V7) as the best ranked variable.

Rank	Argentina		USA		Canada		Singapore		Japan	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
1	V9	V9	V9	V9	V9	V9	V9	V9	V9	V9
2	V3	V3	V3	V3	V3	V3	V10	V10	V7	V8
3	V8	V8	V10	V10	V8	V8	V3	V8	V3	V7
4	V5	V5	V1	V8	V10	V10	V5	V3	V8	V3
5	V7	V16	V8	V1	V7	V7	V8	V11	V1	V11

Table 6.11: Ranking by genders

Furthermore, variabilities were observed within the genders for the least ranked variable. We observed that 18 countries which is 78%, ranked variable 15 (V15) as the least variable, while 3 countries representing 13% ranked variable 17 as the least ranked variable. Moreover, variable 14

(V14) and variable 4 (V4) were both ranked the least variable only by Poland and Luxembourg respectively.

Moreover, it was observed that in some countries, the ranking of the best and least variable by both genders is the same, this means that both genders are indifferent in ranking of the best and least variable. But in some other countries, there are differences in the ranking of the best and least variables between the genders.

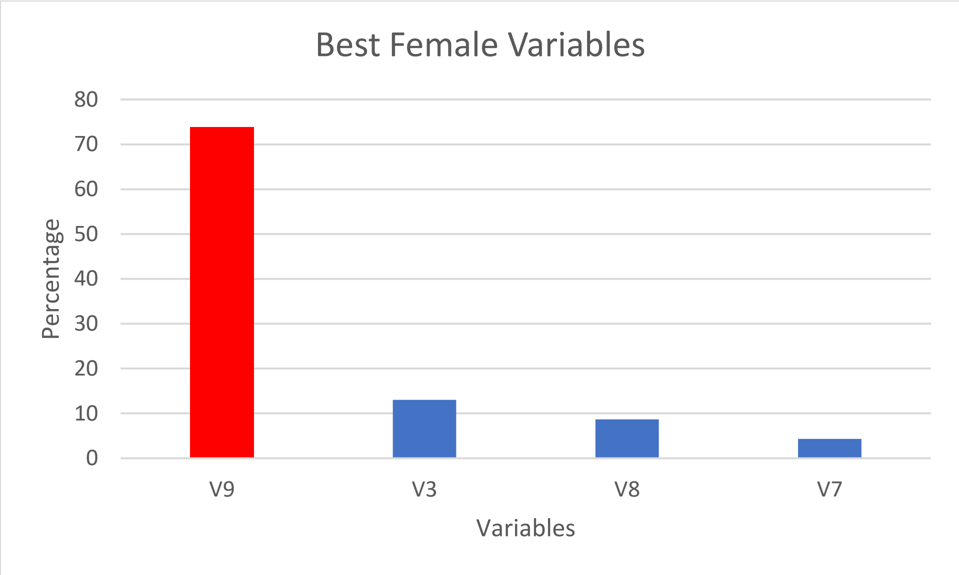


Figure 6.3: Variable ranking by female gender

Rank	India		New Zealand		Italy		UK		Poland	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
1	V9	V9	V9	V9	V3	V3	V9	V9	V9	V9
2	V3	V3	V3	Vv8	V9	V9	V3	VV3	V3	V3
3	V1	V10	V10	V3	V8	V1	V7	V8	V1	V8
4	V10	V1	V7	V10	V1	V10	V10	V10	V7	V1
5	V5	V8	V8	V7	V5	V8	V8	V7	V8	V7

Table 6.12: Ranking by genders

Rank	Netherlands		Germany		Belgium	
	Male	Female	Male	Female	Male	Female
1	V9	V8	V3	V3	V9	V9
2	V8	V9	V9	V8	V3	V3
3	V3	V3	V8	V9	V7	V8
4	V7	V10	V1	V10	V8	V7
5	V10	V7	V10	V1	V1	V10

Table 6.13: Ranking by genders

6.4 Gender Comparison

Table 6.14 below gives an overview of the best ranked variables by country and gender. we observed that variable 9 (offers competitive salary & employee benefit) has been well ranked by both genders and country. This implies that job seekers and employees are highly attracted to companies who can offer them competitive salary and numerous employee benefits. This shows the consistent ranking of variable 9 as the first rank variable.

Variables	Country	Male	Female
V9*	18	20	17
V8	1	0	2
V7	1	1	1
V3	3	2	3

Table 6.14: Best rank by Country and Gender (Male & Female)

In figure 6.4, we see that 86.9% of the males ranked variable 9 as first while 73.9% of the females ranked variable 9 as first. The differences between the ranking of both genders can observed in Switzerland where variable 9 was ranked first by the male gender and variable 8 was ranked first by females.

Furthermore, we observed that in Australia, Russia, Hungary, China, and Canada there are no differences in the ranking of the top five variables by both genders. This means that both genders are indifferent in their ranking. Hence, organisations may adopt same strategy in attracting future employees irrespective of their gender. While in Argentina, same similar ranking was observed with exception to the fifth ranked variable. Variable 7 (V7) was ranked fifth among the makes, but among the female's variable 16 (V16) was ranked fifth.

In Hong Kong, there is a sharp difference in the ranking of the variables between both gender apart from the top ranked variable (V9). For the males in Hog Kong, variables 5, 10, 3, and 1 were ranked 2nd, 3rd, 4th and 5th respectively. While the females ranked variables 10, 8, 1, and 5 as 2nd, 3rd, 4th and 5th respectively. This indicates that for organisations in Hong Kong to be attractive to employees, they must ensure that variables that attract the males and females are considered. However, in Singapore the top two ranked variables (V9 and V10) are the same for both genders. This implies that in Singapore the two most important variables to consider attractive to employees are V9 and 10.

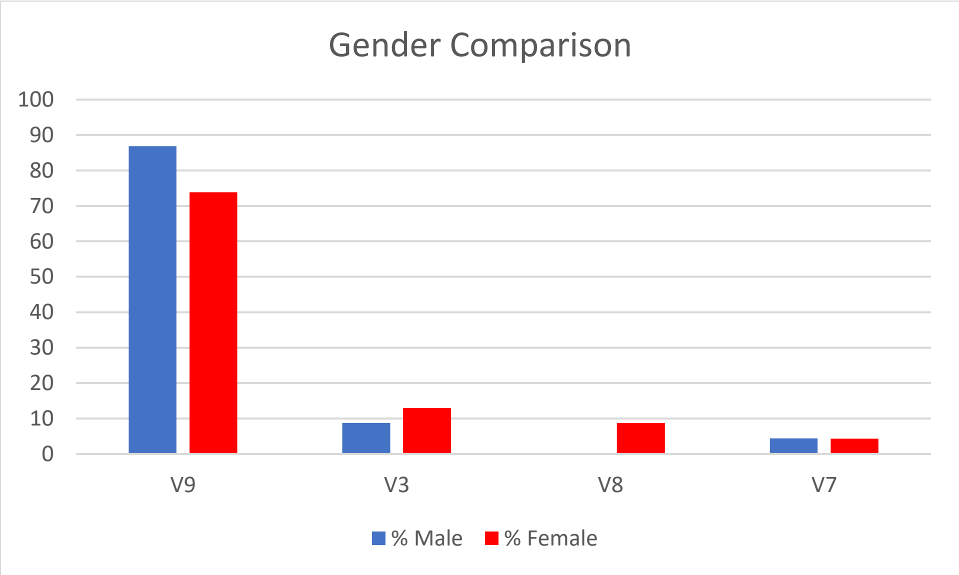


Figure 6.4: Distribution of gender

Moreover, we observed some similarities in the ranking of the top 5 variables among some countries. In France and Belgium, the ranking of the 5 top variables was the same. In both countries, the female genders ranked variable 9 (V9) as the best variable that attracts them most. While variables 3, 7, 8, and 10 were ranked 2nd, 3rd, 4th, and 5th respectively. This indicates that for a multi-national company operation in these countries, similar variables can be adopted to attract female employees. Also, similarities were observed in Canada and United Kingdom (UK). The female genders in both countries ranked variable 9 (V9) as the top attracting variable to consider. Variables 3, 8, 10, and 7 were ranked 2nd, 3rd, 4th, and 5th respectively in both countries. Also, in Australia and Hungary some similarities were seen. Variable 9 (V9) was ranked top in both countries also, while variables 3, 10, 8, and 7 were ranked 2nd, 3rd, 4th, and 5th respectively.

6.5 Correlation Analysis.

The Kendall's rank correlation coefficient was applied to identify the degree of similarity between sets of ranks within a set of objects. The Kendall's rank coefficient is vastly used to determine the relationship between variable rankings.

Table 6.15 below gives the values of Kendall rank coefficient for the twenty-three ranked countries, giving us an insight about the strength of correlation between the seventeen variables in each of the countries. In each country, the seventeen variables were ranked using SPSS which also generates the Kendall's Tau coefficient for each of the countries. We observed that in four countries (Sweden, Hong Kong, USA, and Singapore), the Kendall's tau value is 1.00 which signifies a perfect relationship between the seventeen variables in each of the four countries. However, the United Kingdom (UK) recorded the smallest value (0.745)

Country	Tau Coefficient	Country	Tau Coefficient
Switzerland	0.967	Canada	0.985
Australia	0.971	Singapore	1.00*
Spain	0.985	Japan	0.985
Luxembourg	0.971	India	0.971
Russia	0.956	New Zealand	0.971
Sweden	1.00*	Italy	0.985
Hungary	0.985	UK	0.745
China	0.971	Poland	0.775
France	0.974	Germany	0.985
Hong Kong	1.00*	Netherlands	0.956
Argentina	0.967	Belgium	0.971
USA	1.00*		

Table 6.15: Kendall's Tau coefficients.

Furthermore, figure 6.5 gives us the correlation matrix of the 23 countries, giving us a 23x23 matrix. It was observed that the correlation between a country and itself is 1.00, while the correlation between a country and another differs. The correlation between Switzerland and India gives the smallest correlation with a value of 0.450, which indicates that the correlation between these countries is not very strong and the ranking of the variables in Switzerland and India are not similar. Moreover, the correlation between Switzerland and Luxembourg, Switzerland and Canada have the highest correlation with a value of 0.804 respectively which signifies a very high correlation between them. Furthermore, Switzerland has a high correlation with the following countries; Australia (0.745), Spain (0.686), Sweden (0.775), Hungary (0.731), France (0.776), US (0.701), New Zealand (0.745), Germany (0.790), Netherlands (0.790) and Belgium (0.775). The correlation value indicates that the ranking of the seventeen variables in Switzerland and the other ten countries are similar signifying only a little difference in their ranks.

Figure 6.5 below gives us the graph of the top five variables in the thirteen European countries, with the horizontal axis giving us the thirteen countries while the vertical axis termed weight is the ranks of the variables/factors. Figure 6.5 is divided into three parts, Group 1 and Group 2 are countries with the same colour profiles, while 'Others' contains countries with different colour profiles.

It was observed that in Group 1, all the six countries (France, Hungary, Luxembourg, Netherland, Belgium, and the United Kingdom) have the same colour profiles. We observed that variable 9 (V9) which represents 'offers competitive salary and employee benefits' has the highest bar across the six countries. This indicates that employees are attracted to organisations that can pay them competitive salary obtainable in the industry. While the bar of variable 8 (V8) which represents 'pleasant work experience' has the lowest height (ranked 5th) in this group. In Group 2, it was observed that two countries (Germany and Italy) have the same colour profiles which represents similar ranking. In this group, we observed that variable 3 (V3) which represents 'long-term job security' has the highest bar in both countries (ranked 1st). This indicates that in these two European countries, employees and future employees are attracted to organisations that can offer them job security. When employees perceive that there is no job security in an organisation, they are generally not attracted to such organisations because they might be laid off after few years of employment. However, it was observed that variable 1 (V1) which represents 'financially healthy' has the lowest bar (ranked 5th).

Furthermore, the third group termed 'Others' consists of five countries (Poland, Russia, Spain, Sweden, and Switzerland) with different colour profiles each. This indicates that the ranking of the top five variables in these countries are different. In these countries (Poland, Russia, Spain, and Switzerland) except Sweden, the variable 'competitive salary and employee benefit' (V9) has the highest bar being ranked 1st. However, in Poland and Russia, the variables 7 and 5 which represents 'interesting job content' and 'career progression' were ranked 5th in both countries. Also, in Spain and Switzerland, 'interesting job content' (V7) and 'offers flexible working arrangement' (V16) were ranked 5th.

Moreover, it was observed that in Sweden, 'Job Content' (V7) with the red bar has been ranked first (with the highest bar), this means that employees and jobseekers in Sweden are attracted to organisations that can offer them interesting job content. Also, we noted that variable 11 (V11) which is 'conveniently located' which we termed 'Location was ranked least (5th). This is to say employees are more attracted to interesting job content that the location of the organisation.

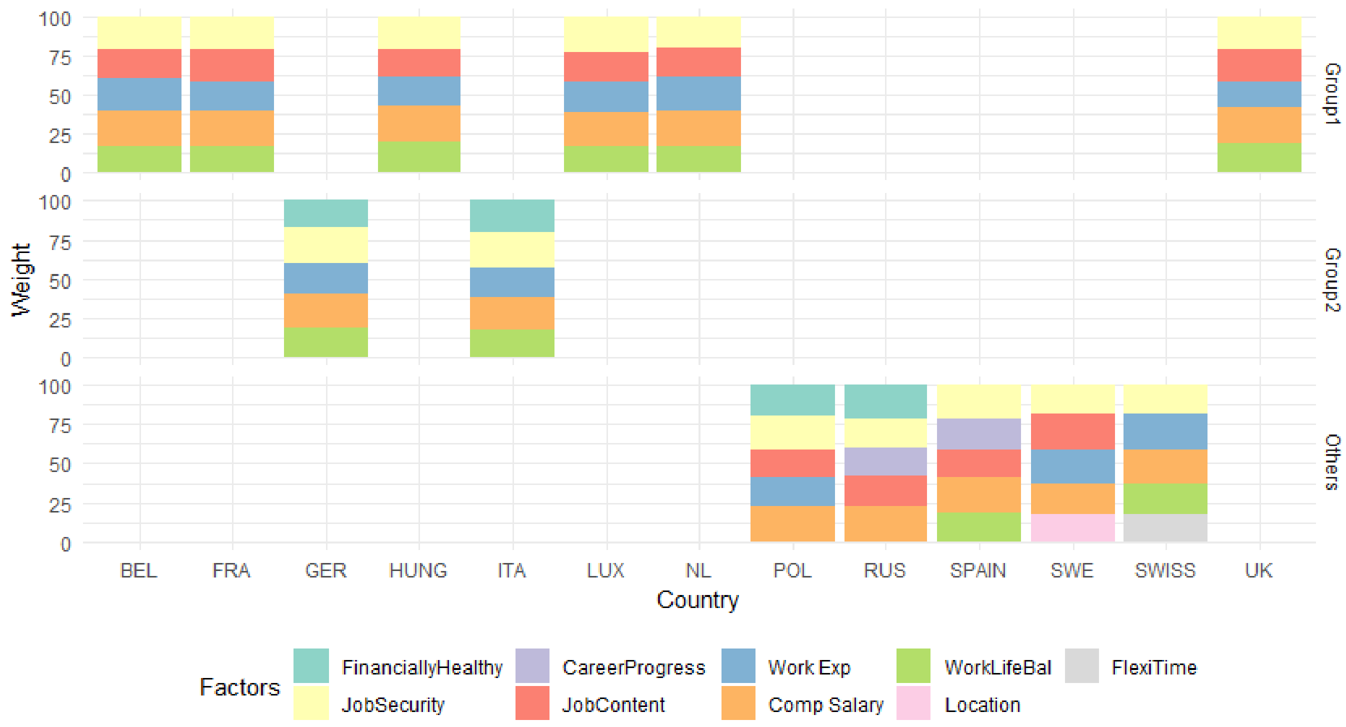


Figure 6.5

Comparison

Across the three different groups, some differences were observed. It was observed that across the thirteen countries in Europe, variable 11 which represents 'is conveniently located' which we termed 'location' was not attractive to employees but only in Sweden which was also ranked fifth. While variable 16 which is 'offers flexible working arrangements' which we term 'FlexTime' was only attractive fifth in Switzerland and ranked fifth.

In Group 1, variable 7 which is 'interesting job content' was ranked among the top five variables in this group but not listed among the top five in Group 2. While in Group 2, variable 1 'financially healthy' was ranked among the top five in group 2 but not in group 1. This differences in ranking shows the differences across the countries. Hence, decision-makers should always take into account country specific differences.

6.6 TOPSIS and Mean Comparison Based on Country

A comparison between the results of TOPSIS and Mean (Average) reveals some differences between the ranking of the variables by the two methods. Tables 6.2 to 6.6 gives us the ranking of the seventeen variables by TOPSIS and Mean (Average), from the tables we can see that there are some differences as well as similarities between the countries.

In table 6.2, it was observed that in Switzerland, Australia, Spain, Luxembourg, and Russia there was no difference in the ranking of the variables by TOPIS method and Mean (Average) for the best five ranked variables. Also, in tables 6.3 to 6.6 we also observed that in the following countries; Sweden, Hungary, Hong Kong, USA, Canada, Singapore, Japan, India, New Zealand, Germany, and Belgium, there was no difference in the ranking of the variables in the two methods. This implies that in the ranking of the best five variables in these countries, the method of ranking used does not make a difference because they both produce the same ranking results for the best five variables.

Rank	France		Poland		Italy	
	M-TOPSIS	Mean	M-TOPSIS	Mean	M-TOPSIS	Mean
1	V9	V9	V9	V9	V3	V3
2	V3	V3	V3	V3	V9	V9
3	V7	V8	V1	V8	V1	V8
4	V8	V7	V8	V1	V8	V1
5	V10	V10	V10	V10	V7	V7

Table 6:16:

In table 6:16, we observed some switching in the ranking of France, Poland, and Italy. We can see that the ranking of the 1st, 2nd and 5th positions in these countries did not change irrespective of the method applied. However, we noticed the switching between the 3rd and 4th ranking of these countries. In France, the 3rd best variable with TOPSIS method became the 4th best ranked variable when we use Mean (Average) method and vice versa. Similarly, same observation was seen in Poland and Italy, variable 1 (V1) which is the 3rd best ranked variable in Poland and Italy with TOPSIS became the 4th best ranked variable when we use the Mean method and vice versa.

Furthermore, in UK and Argentina the ranking of the best four variables in these countries were similar irrespective of the method deployed. However, the difference is in the fifth ranked variables. In UK the 5th ranked variable with the TOPSIS method is variable 8 (V8), while with the Mean method variable 7 (V7) was the 5th ranked variable. In Argentina, the fifth ranked variable with the TOPSIS method was Variable 7 (V7), while with the Mean method it was variable 16.

Lastly, we see in China and Netherlands the difference is in the switching of the 4th and 5th positions in the two methods. In China, the 4th best ranked variable (V1) with TOPSIS method became the fifth best ranked with Mean method and vice versa. While in Netherlands, the 4th best ranked variable (V7) with TOPSIS method became the 5th best ranked variable with the Mean method.

7.0 Conclusion and Recommendation

7.1 Conclusion

In this thesis, a systematic review and evaluation of existing and current research was conducted in a view of finding answers to the two main research questions.

During the research, the results showed as expected some differences in the ranking of the Modified-TOPSIS and the Mean (Average) method, where in most cases the Modified-TOPSIS ranks better than the mean method with the use of the relative distances. Based on this finding, we can argue that the use of Modified-TOPSIS method will improve the decision-making choices of managers.

Hence, it important for organisations to ensure that their decision-making methods aligns with the organisation goals and objectives. Also, there were some similarities in the ranking of both methods which was noticed in table 6.2, were it was observed that the ranking of the Modified-TOPSIS for a country was the same when we used the Mean method. This shows that irrespective of the method used, the ranking of the best five variables in these countries does not change.

Furthermore, we observed some differences and similarities in the ranking between the genders. Variable 9 (V9) has been ranked by both genders as the best variable except in Italy, Germany, Netherlands, and Switzerland. This is to say in majority of the countries, both genders are indifferent in the ranking of the best variable. In Germany and Italy, variable 3 (V3) was ranked as the best variable which shows difference in ranking of the gender. while in Netherlands, and Switzerland, there is a similarity in the ranking of best variable in these two countries based on gender. Variable 9 (V9) has been ranked as best variables in both Netherlands and Switzerland by the male gender while the female gender in both countries ranked variable 8 (V8) as the best ranked variable. This is to say the males in Switzerland and Netherlands will prefer V9 "Offers competitive salary & employee benefit" as the first attractive factor. While for the females, the first attractive factor to consider is V8 "has a pleasant working atmosphere".

However, for organisations to be both competitive and attractive to employees and future employees in Europe, variables such as competitive salary and job security should be given priority because they are the two top variables that attract employees.

7.2 Recommendation

This research could be of importance to a purposeful reader because it provides new insights about the novel approach Modified-TOPSIS provides to decision-makers and how it enhances their decision choices. Different from the commonly used means (average) and conventional TOPSIS method, the modified-TOPSIS has not been fully utilized by companies, hence the results presented in this thesis can be used as a starting point to further evaluate effective decision-making choice.

This research has a twofold contribution which also provides valuable awareness. The results presented in chapter six adds to the already existing evidence that the modified-TOPSIS method provides a robust solution for decision-makers. The analysis was carried out based on country and gender only, however, other factors such as education, industry, and age are recommended to validate the findings.

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Appendix 1: Lists of Tables

Variable	Switzerland	Australia	Spain	Luxembourg	Russia	Sweden	Hungary
V1	8	7	8	6	2	9	7
V2	10	10	9	10	14	10	10
V3	4	2	2	1	4	4	2
V4	16	16	13	16	13	15	13
V5	8	8	3	7	5	8	6
V6	14	11	12	11	10	12	12
V7	6	5	5	4	3	1	5
V8	1	4	6	3	7	2	4
V9	2	1	1	2	1	3	1
V10	3	3	4	5	6	6	3
V11	9	6	10	9	8	5	9
V12	15	12	16	14	11	14	15
V13	11	13	11	12	15	11	11
V14	13	14	15	13	17	13	16
V15	17	17	14	17	16	17	14
V16	5	9	7	8	9	7	8
V17	12	15	17	15	12	16	17

Variable	China	France	Hong Kong	Argentina	USA	Canada	Singapore	Japan
V1	4	7	5	8	5	7	6	7
V2	8	10	9	9	10	10	11	12
V3	3	2	6	2	2	2	3	4
V4	14	13	14	10	16	16	12	15
V5	2	6	2	4	6	6	5	9
V6	9	13	11	17	11	11	9	10
V7	7	3	7	5	5	5	8	2
V8	6	4	4	3	3	3	4	3
V9	1	1	1	1	1	1	1	1
V10	5	5	3	7	4	4	2	6
V11	11	9	8	11	8	8	7	5
V12	10	13	12	14	13	13	13	11
V13	13	11	13	14	12	12	15	13
V14	16	16	15	12	14	14	17	17
V15	15	17	17	15	17	17	16	16
V16	12	8	10	6	9	9	10	8
V17	17	15	16	16	15	15	14	14

Variable	India	New Zealand	Italy	UK	Poland	Germany	Netherlands	Belgium
V1	3	8	3	8	3	5	6	7
V2	12	10	10	10	10	11	11	10
V3	2	2	1	2	2	1	3	2
V4	8	15	12	14	12	13	16	15
V5	5	6	6	7	7	7	8	9
V6	7	11	13	11	13	12	12	12
V7	9	5	7	3	5	8	4	4
V8	6	4	4	5	4	3	2	3
V9	1	1	2	1	1	2	1	1
V10	4	3	5	4	6	4	5	5
V11	13	7	8	6	8	9	9	6
V12	15	12	15	12	15	16	13	14
V13	14	13	11	13	11	10	10	11
V14	16	14	16	16	17	14	14	13
V15	11	17	14	17	14	17	15	16
V16	10	9	9	9	9	6	7	8
V17	17	16	1	1	1	15	17	17

Rank	Germany		Netherlands		Belgium	
	M-TOPSIS	Mean	M-TOPSIS	Mean	M-TOPSIS	Mean
1	V3	V3	V9	V9	V9	V9
2	V9	V9	V8	V8	V3	V3
3	V8	V8	V3	V3	V8	V8
4	V10	V10	V7	V10	V7	V7
5	V1	V1	V10	V7	V10	V10
6	V16	V16	V1	V1	V11	V11
7	V5	V5	V16	V16	V1	V1
8	V7	V7	V5	V5	V16	V16
9	V11	V11	V11	V11	V5	V5
10	V13	V2	V13	V2	V2	V2

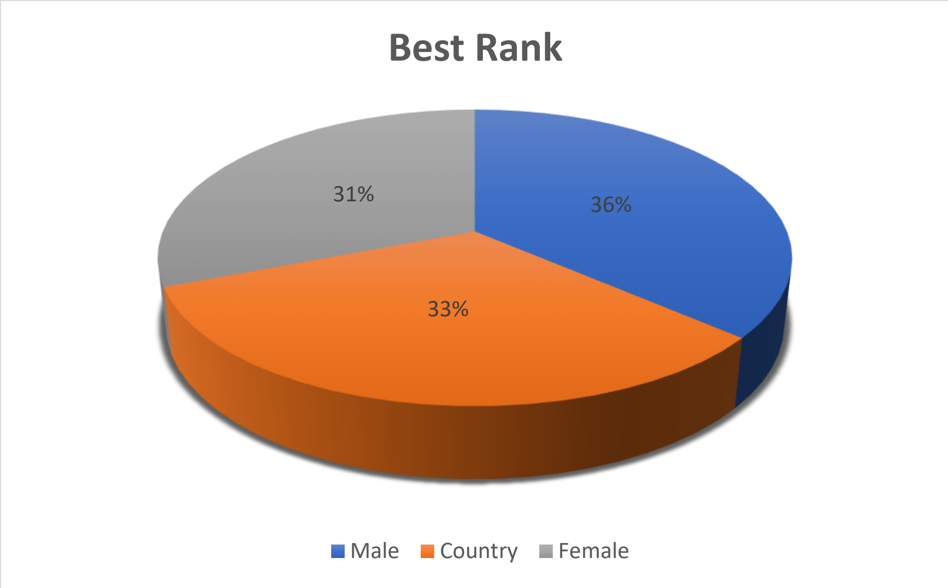
Appendix 2: Country and Gender Distribution of Variables

Variables	Country	Male	Female
V17	7	10	3
V15	9	3	18
V14	6	9	1
V6	1	1	0
V4	0	0	1

Appendix 3: Applications of TOPSIS. Adapted from H.S Shih

No	Application Areas	Number Of Attributes	Number of Alternatives	Proposed by
1	Company financial ratios comparison	4	7	Deng et al
2	Expatriate host country selection	6 (with 25 sub-attributes)	10	Cheng & Tzeng
3	Facility location selection	5	4	Chu
4	Gear material selection	5	9	Milani et al
5	High-speed transport system selection	15	3	Janic
6	Manufacturing plant location analysis	5 (with 16 sub-attributes)	5	Yoon & Hwang
7	Multiple response selection	2	18	Yang & Chou
8	Rapid prototyping-process selection	6	6	Byun & Lee
9	Robot selection	4	27	Parkan & Wu
10	Solid waste management	12	11	Cheng et al
11	Water management	6 (with 3 demand points)	12	Srdjevic et al

Appendix 4: Percentage distribution of variable 9



Appendix 5: Correlation Matrix

	SWISS	AUST	SPAIN	LUX	RUS	SWE	HUN	CHIN	FRA	HK	ARG	US	CAN	SING	JAP	IND	NZ	ITA	UK	POL	GER	NL	BEL
SWISS	1.000	.745**	.686**	.804**	.539**	.775**	.731**	.524**	.776**	.672**	.667**	.701**	.804**	.642**	.686**	.450*	.745**	.563**	.593**	.578**	.790**	.790**	.775**
AUST	.745**	1.000	.721**	.882**	.706**	.779**	.824**	.706**	.810**	.794**	.627**	.868**	.926**	.765**	.824**	.588**	.956**	.583**	.745**	.598**	.750**	.809**	.882**
SPAIN	.686**	.721**	1.000	.750**	.632**	.706**	.897**	.750**	.810**	.750**	.775**	.735**	.765**	.721**	.632**	.691**	.765**	.568**	.554**	.554**	.765**	.735**	.750**
LUX	.804**	.882**	.750**	1.000	.676**	.779**	.824**	.647**	.870**	.735**	.701**	.809**	.926**	.706**	.765**	.588**	.868**	.613**	.657**	.627**	.838**	.868**	.882**
RUS	.539**	.706**	.632**	.676**	1.000	.574**	.647**	.676**	.691**	.706**	.509**	.750**	.691**	.735**	.765**	.618**	.691**	.583**	.627**	.627**	.574**	.603**	.618**
SWE	.775**	.779**	.706**	.779**	.574**	1.000	.721**	.544**	.796**	.662**	.627**	.647**	.794**	.603**	.809**	.426*	.794**	.450*	.613**	.494**	.706**	.794**	.868**
HUNG	.731**	.824**	.897**	.824**	.647**	.721**	1.000	.735**	.885**	.765**	.731**	.809**	.868**	.794**	.706**	.706**	.868**	.642**	.627**	.657**	.809**	.838**	.824**
CHIN	.524**	.706**	.750**	.647**	.676**	.544**	.735**	1.000	.662**	.824**	.598**	.750**	.721**	.735**	.588**	.706**	.750**	.524**	.509**	.509**	.632**	.632**	.647**
FRA	.776**	.810**	.810**	.870**	.691**	.796**	.885**	.662**	1.000	.751**	.761**	.796**	.885**	.766**	.781**	.587**	.855**	.627**	.702**	.672**	.810**	.855**	.840**
HK	.672**	.794**	.750**	.735**	.706**	.662**	.765**	.824**	.751**	1.000	.627**	.809**	.809**	.794**	.676**	.588**	.838**	.524**	.598**	.509**	.721**	.721**	.706**
ARG	.667**	.627**	.775**	.701**	.509**	.627**	.731**	.598**	.761**	.627**	1.000	.613**	.686**	.627**	.539**	.554**	.672**	.489**	.489**	.504**	.686**	.686**	.701**
US	.701**	.868**	.735**	.809**	.750**	.647**	.809**	.750**	.796**	.809**	.613**	1.000	.853**	.868**	.779**	.632**	.853**	.657**	.672**	.642**	.765**	.765**	.750**
CAN	.804**	.926**	.765**	.926**	.691**	.794**	.868**	.721**	.885**	.809**	.686**	.853**	1.000	.779**	.779**	.603**	.941**	.627**	.701**	.642**	.794**	.853**	.868**
SING	.642**	.765**	.721**	.706**	.735**	.603**	.794**	.735**	.766**	.794**	.627**	.868**	.779**	1.000	.706**	.676**	.809**	.613**	.627**	.598**	.721**	.662**	.676**
JAP	.686**	.824**	.632**	.765**	.765**	.809**	.706**	.588**	.781**	.676**	.539**	.779**	.779**	.706**	1.000	.500**	.779**	.524**	.686**	.568**	.662**	.750**	.794**
IND	.450*	.588**	.691**	.588**	.618**	.426*	.706**	.706**	.587**	.588**	.554**	.632**	.603**	.676**	.500**	1.000	.603**	.494**	.362*	.480**	.603**	.574**	.559**
NZ	.745**	.956**	.765**	.868**	.691**	.794**	.868**	.750**	.855**	.838**	.672**	.853**	.941**	.809**	.779**	.603**	1.000	.568**	.731**	.583**	.765**	.824**	.868**
ITA	.563**	.583**	.568**	.613**	.583**	.450*	.642**	.524**	.627**	.524**	.489**	.657**	.627**	.613**	.524**	.494**	.568**	1.000	.741**	.948**	.657**	.539**	.554**
UK	.593**	.745**	.554**	.657**	.627**	.613**	.627**	.509**	.702**	.598**	.489**	.672**	.701**	.627**	.686**	.362*	.731**	.741**	1.000	.793**	.554**	.583**	.657**
POL	.578**	.598**	.554**	.627**	.627**	.494**	.657**	.509**	.672**	.509**	.504**	.642**	.642**	.598**	.568**	.480**	.583**	.948**	.793**	1.000	.613**	.583**	.598**
GER	.790**	.750**	.765**	.838**	.574**	.706**	.809**	.632**	.810**	.721**	.686**	.765**	.794**	.721**	.662**	.603**	.765**	.657**	.554**	.613**	1.000	.824**	.809**
NL	.790**	.809**	.735**	.868**	.603**	.794**	.838**	.632**	.855**	.721**	.686**	.765**	.853**	.662**	.750**	.574**	.824**	.539**	.583**	.583**	.824**	1.000	.897**
BEL	.775**	.882**	.750**	.882**	.618**	.868**	.824**	.647**	.840**	.706**	.701**	.750**	.868**	.676**	.794**	.559**	.868**	.554**	.657**	.598**	.809**	.897**	1.000