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**DECISION FRAMEWORK ON SELECTING THE OPTIMAL
SUBJECTIVE WEIGHTING METHOD FOR EVALUATING
E-LEARNING APPROACHES**



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Abstrak

Pembuatan Keputusan Berbilang Kriteria (MCDM) merujuk kepada membuat keputusan dengan kehadiran beberapa kriteria atau objektif. Pemberat kriteria khususnya pemberat subjektif mempunyai pengaruh yang besar pada keputusan kerana kaedah pemberat yang berlainan boleh menghasilkan pemberat dan pemangkatan yang berbeza bagi masalah yang sama. Tambahan pula, perbandingan berpasangan (PCs) dalam Proses Hierarki Analitik (AHP) sering tidak konsisten dalam pertimbangan yang memaksa pembuat keputusan untuk mengkaji semula pertimbangan. Kajian ini bertujuan untuk membangunkan kerangka keputusan dalam memilih kaedah pemberat subjektif (SW) yang optimal untuk dimanfaatkan dalam penilaian lima pendekatan e-pembelajaran. Di samping itu, kajian ini mencadangkan Hubungan Tripartit untuk Mengatasi Ketidakkonsistenan (TROI) bagi mengatasi masalah ketidakkonsistenan dalam PCs. Prestasi sembilan teknik pemberat subjektif termasuk kaedah PC telah dibandingkan terhadap lima kriteria e-pembelajaran yang telah dikenalpasti. Selanjutnya, kajian ini juga menunjukkan penggunaan kaedah TROI untuk memproses ketidakkonsistenan dalam AHP. Pada asasnya, kaedah TROI menggunakan baris pertama matrik PC yang tidak konsisten untuk menjana unsur pada baris selainya. Seramai 95 peserta dari sebuah universiti terpilih telah menilai kepentingan kriteria dan kualiti setiap kriteria bagi setiap lima pendekatan e-pembelajaran. Kaedah SW yang optimal mempunyai nilai pemberat dengan jumlah perbezaan mutlak yang terendah berbanding purata geometri semua pemberat. Pemberat yang optimal kemudiannya digunakan untuk memilih pendekatan e-pembelajaran yang paling sesuai dengan menggunakan Teknik Untuk Keutamaan Ikut Serasian Ideal (TOPSIS). Hasil kajian menunjukkan bahawa Pemberat Bergrafik adalah kaedah SW yang optimal, manakala Bilik Darjah Terbalik adalah jenis e-pembelajaran yang paling sesuai untuk pelaksanaan di universiti terpilih. Kaedah TROI yang dicadangkan telah membantu menangani 12 pertimbangan yang tidak konsisten dalam matriks PC, manakala kaedah PC yang baharu iaitu PC-TROI, telah dibangunkan untuk mencapai pertimbangan yang konsisten. Kajian ini telah berjaya membangunkan satu kerangka keputusan untuk membantu pembuat keputusan dalam memilih kaedah SW yang optimal, di samping mencadangkan kaedah alternatif kepada AHP.

Kata kunci: Kriteria pemberat, E-pembelajaran, Subjektif, Perbandingan berpasangan, Tidak konsisten

Abstract

Multi-Criteria Decision Making (MCDM) refers to making decisions in the presence of several criteria or objectives. The criteria weights particularly the subjective weights have great influence on the decisions since different weighting methods may yield different weights and ranking on the same problem. Furthermore, the Pairwise Comparisons (PCs) in Analytic Hierarchy Process (AHP) often encounter inconsistency in judgment which forces the decision maker(s) to revise the judgments. This study aims to develop a decision framework for selecting the optimal subjective weighting (SW) method to be applied in the evaluation of five e-learning approaches. Besides, this study proposes the Tripartite Relations for Overcoming Inconsistency (TROI) to address the inconsistency problem in PCs. The performances of nine SW techniques including PCs method on five identified e-learning criteria were compared. Moreover, this study also demonstrates the application of TROI method for processing inconsistency in AHP. Basically, the TROI method would use the first row of the inconsistent PC matrix to generate elements of the rest of the rows. A total of 95 participants in a selected university evaluated the importance of the criteria and rated the quality of each criterion for each of the five e-learning approaches. The optimal SW method has weights with the least total absolute differences compared to the geometric mean of all nine weights. The optimal weight was then used to select the most suitable e-learning approach by using Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method. The results of the study show that Graphical Weights is the optimal SW method, while Flipped Classroom is the most appropriate type of e-learning for implementation in the selected university. The proposed TROI method has helped addressing 12 inconsistent judgments in the PC matrices, while a new PC method, PC-TROI, has been established to achieve a consistent pairwise judgment. This study has successfully developed a decision framework to aid decision maker(s) in choosing the optimal SW method while proposing alternative method to AHP.

Keywords: Criteria weights, E-learning, Subjective, Pairwise comparison, Inconsistency

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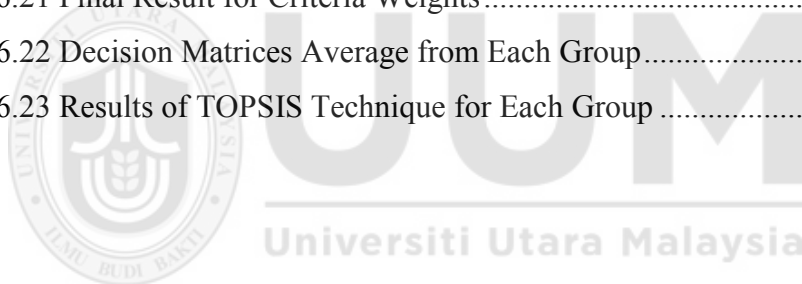
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List of Abbreviations

AHP	Analytic Hierarchy Process
ANP	Analytic Network Process
CI	Consistency Index
CR	Consistency Ratio
CRITIC	Criteria Importance through Inter criteria Correlation
DMs	Decision-Makers
DPA	Direct Point Allocation Weights Method
ELECTRE	Elimination and Choice Translating Reality
G. Mean	Geometric Mean
GW	Graphical Weighting Method
ICT	Information and Communication Technology
IT	Information Technology
IW	Ideal Weights
MADM	Multi-Attribute Decision-Making
MATLAB	Matrix Laboratory language program
MAUT	Multi-Attribute Utility Theory
MCDM	Multi-Criteria Decision-Making
MDDM	Multi-Dimension Decision-Making
MODM	Multi-Objective Decision-Making
PCs	Pairwise Comparisons
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluations
RE	Rank Exponent Weight Method
RI	Random Index
RM	Rating Method
ROC	Rank Order Centroid Weight Method
RR	Reciprocal Weight Method
RS	Rank Sum Weight Method
RW	Ratio Weighting Method

SDs	Standard Deviation Method
SMART	Simple Multi-Attribute Rating Technique
TOPSIS	The Technique for Order Preference by Similarity to Ideal Solutions
TROI	Tripartite Relations for Overcoming Inconsistency
UUM	Universiti Utara Malaysia
WPM	Weighted Product Model
WSM	Weighted Sum Model



CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Decision making is necessary for people and usually becomes complicated in the existence of uncertainty. In any project, decision framework is required for making effective decisions. The framework is a basic conceptional structure, or it is a system of rules or ideas that are used to plan or decide something. A decision framework has four phases: Preparation (identifying the problem, determining goals, gathering information and analyzing data), decision (the specific process of creating a determination), implementation (the actions were taken as a direct result of the decision) and consequences (the effects created by the implementation actions) (G. H. Tzeng & Huang, 2011).

Multi-criteria Decision Making (MCDM) describes making decisions in the presence of several criteria or objectives. MCDM is taken into consideration to be an important and active area of research. In MCDM, a decision maker (DM) defines the goals which he/she wishes to achieve; the problem is then formulated, and alternatives are discovered. These alternatives are then evaluated against each criterion and eventually prioritized. The following subsections describes the decision framework in MCDM techniques regarding this study.

1.1.1 Multi-Criteria Techniques

In MCDM techniques, the weights of the evaluation criteria should be determined in advance. Multi-Criteria problems include criteria of differing importance to DMs. Then, details regarding the relative importance of the criteria are needed, and this

typically realized by assigning a weight to each criterion (Ananda & Herath, 2005; Malczewski, 1999). Therefore, the derivation of weights is the main step in generating the DM's preferences. For that, a weight can be defined as a value allocated to an assessment criterion that shows its importance about other criteria.

The MCDM techniques are defined by the need to assess a limited set of alternatives on multiple attributes. The principal aim in utilizing MCDM techniques is to evaluate the preference values of the alternatives on some allowable scale. In the MCDM methods, alternatives are assessed on each of the attributes to get the priority values for solving MCDM problems. Furthermore, whether the weights of criteria will affect MCDM results positively or negatively relies upon how the DM evaluate criteria. The criteria play a major role in the selection of alternatives. For that, the weights of criteria have great importance in solving MCDM problems.

In mainstream MCDM techniques, allocating weights to the assessment criteria or alternatives is an essential step. The weighting methods classified by Wang et al. (2009) into three categories: subjective, objective, and combination (integrated) weighting methods. Assign of criteria weights in subjective weights methods are based on the preferences of the DMs (use judgments of DM). In the objective weights methods, assign criteria weights are based on the analysis of initial data (through mathematical calculation). The weights in combined or integrated weighting methods are stemmed from the information through subjective and objective together on attributes weights. This study focuses on subjective weighting methods to assess attributes based on derivation by the DM's judgments or based on their experience and knowledge in the relevant field.

From literature, several subjective weighting methods were proposed in previous studies and applied for solving various MCDM problems. For instance, pairwise comparisons, rating, ranking, trade-off analysis, ratio and point allocation are some popular weighting methods. However, each of these methods is different in regards to accuracy, theoretical foundations, intricacy for users, as well as ease of use, which yields various sets or rank of attributes weights. Therefore, choosing an appropriate weighting technique is an essential matter in addressing MCDM problems (Zardari, Ahmed, Shirazi, & Yusop, 2015). Hence, many researchers recommended that the definition of attributes significance should be well comprehended by all DMs. Zardari et al. (2015) pointed out that the real meaning of criteria weights achieved by using the average of various weighting methods is necessary for avoiding any inaccurate weights of the MCDM methods and obtaining positive outcomes.

Based on the literature, different weights methods may yield different ranking for criteria on the same problem. Therefore, the validity of these attributes weights are essential in determining weights by utilizing various weighting methods for preventing any type of abuse of the MCDM techniques, as well as obtaining dependable outcomes (Wang, Jing, Zhang, & Zhao, 2009). Assigning weights of criteria is an essential step in solving MCDM problems. For that, selecting the best weights method is necessary for avoiding any inaccurate weights of the MCDM methods and obtaining positive outcomes (Zardari, Ahmed, Shirazi, & Yusop, 2015). A decision framework for selecting a proper weighting method is needed through comparison of various subjective weights methods including Pairwise Comparisons method (PCs) or Analytic Hierarchy Process (AHP) which has inconsistency problem.

A priority ranking criteria was established based on the survey conducted through a questionnaire distributed among the participants. In this study, nine of subjective weighting methods were used to assign attributes weights based on the preferences of the DMs (i.e. Rating (RM), Rank Order Centroid (ROC), Rank Exponent (RE), Rank Reciprocal (RR), Rank Sum (RS), Ratio (RW), Graphical Weights (GW), Direct Point Allocation (DPA), and Pairwise Comparisons (PCs)). Schoemaker and Waid (1982) found that the various methods on the same problem yielded significantly different weights estimates. Therefore, this study developed a decision framework to aid DMs in choosing the optimal weighting method for solving MCDM problems.

On the other hand, the Pairwise Comparison (PCs) method needs to have a consistency test. Normally, if consistency ratio is less than 0.1, then the criteria weights will be acceptable or consistent. Meanwhile, inconsistency occurs when the ratio indicates more than 0.1. In inconsistency cases, the researchers need to go back to DMs to get new scores or ranks about the criteria. So, it will be a difficult mission for the researchers if the criteria weights are inconsistency. This study presented proposed method for overcoming this problem without the need to revise from DMs; known as Tripartite Relations for Overcoming Inconsistency (TROI).

1.1.2 E-Learning in Higher Education

The world has become a global village due to the significant technological development. The transformation is due to the fact that people are able to access relevant information from anywhere in the world. Furthermore, Information Technology (IT) has a significant impact on societies.

The fast-paced growth of internet service has brought about a new context for learning objectives. As a result of the rapid increase in using of modern technology, the internet has come to be a major factor in several universities due to its importance for administrative, academic staff, as well as students (Llorens, Salanova, & Grau, 2002). The internet has without a doubt turned into one of the essential instructional tools, and the most efficient means of communication in universities. In the same context, there is still a shortage of effective use of instructional technology in the educational process (Wang & Chen, 2008).

Prevailing traditional learning methods are obsolete because of the emergence of IT. Therefore, universities of Malaysia are likely to lead toward educational reforms that are necessary for keeping up with the Information Communication Technologies (ICT) evolution. According to Resta (2005), e-learning plays a significantly important role in developing the instructional growth and preparing a new generation of educators in higher educational establishments. Consequently, it is expected that with the application of e-learning, teaching techniques are going to be transformed. This indicates not only modifications in course models but also in perspectives, in order to recognize the new challenges posed by e-learning approaches in general and higher education in particular (McPherson & Nunes, 2002).

Consequently, e-learning can offer as a stimulant for modification in teaching and learning. Therefore, e-learning supports skills required in knowledge-based society, like collecting, analysing (evaluating) and using information properly. It includes various teaching techniques, for instance, information management, collaborative learning, critical thinking, creative thinking, and problem-solving. Implementation

strategic of e-learning at universities can attenuate the effects of some changes which are very often results of the state policy and economic situation towards higher education: (1) increased number of students and therefore lack of student-professor interaction, (2) broadened teaching and learning requirements and as a result lack of time for students' learning, (3) lack of time for scientific research of academic staff (Begičević, Divjak, & Hunjak, 2007).

In general, lecturers (academic staff) are required to do even more with less, teach more students, supervise more research students, publicize increasingly more relevant research results, and so forth (Begičević et al., 2007). In other words, every comprehensive university has a three folded goals: teaching, research, and also service to society. E-learning system is an effective tool for accomplishing strategic goals of the university (Divjak & Begičević, 2006). It contributes to the solution on the level of the organization as well as the personal level (lecturers and students). The universities in Malaysia seek to strategically implement e-learning in the existing academic activities because of many practical benefits that e-learning brings.

1.1.3 E-Learning Approaches

With the proliferation of ICT and its beneficial uses in the educational sector in Malaysia, a lot of the academic staff in Malaysia universities are novice technology users, who use computers only for the fundamental functions, like PowerPoint presentation and word processing (Aldojan, 2006). Technology alone might not be the answer to all of the universities' problems (Daniel, 1996).

Modern learning strategy concentrates on the direct interaction between students and positive learning techniques with guidance from the lecturer including the student's ability to participating and researching. Also, there is a need to develop teaching methods, strategies and the use of modern teaching strategies based on the employment of modern technologies in the development of the educational process (Strayer, 2007). Universities in Malaysia are in the move of implementing ICT in their teaching and learning activities.

The novel approaches that rely on the use of modern technology to activate the digital learning strategies are distance learning that includes synchronous and asynchronous learning, blended learning, flipped classroom and ICT supported face to face learning (Begičević, Divjak, & Hunjak, 2007; Kim, Heo, & Lee, 2015; Manca & Ranieri, 2016). Flipped classroom has taken place in education as a modern teaching method (Osman, Jamaludin, & Mokhtar, 2014). It is a shift in the process from teacher-centred learning to student-centred learning (Galindo, 2014). Flipped classroom is a concept for active learning where students are provided with study materials like video lectures or online textbooks before they attend the class (Bishop & Verleger, 2013). Another method of modern teaching methods is a blended learning. It blends processes of traditional learning and e-learning (Dos, 2014). E-learning is usually defined as a distance learning that includes synchronous learning and asynchronous learning, and sometimes, it is also described as a type of learning supported by ICT (Begičević et al., 2007; Chao & Chen, 2009).

As a developing country, Malaysia is still having problems to keep up with the ICT evolution due to lack of resources, infrastructure, and readiness compared with

developed countries in the application field of e-learning such as America, England, Australia, etc. Despite of the growth of e-learning practices, there are few quantitative types of research being conducted focusing on e-learning approaches. The aim of this study is to evaluate five of e-learning approaches namely: ICT supported traditional education, flipped classroom, blended learning, synchronous learning and asynchronous learning, and select the best approach based on five identified criteria by using multi criteria methods, in order to be applied in the chosen university in Malaysia.

1.2 Problem Statement

The MCDM is an emerging discipline which supports decision makers who face multiple and usually conflicting criteria. MCDM allows DMs to select and rank alternatives according to different and conflicting criteria and is classified on the major components in the decision-making. The weights of criteria should be determined prior to evaluating the alternatives. This task could be carried out with the help of experts or DMs to give weights of criteria. On the other hand, there are several weighting methods to determine criteria weights, each of these methods is different regarding accuracy, theoretical foundations, complexity for users and ease of use, as well as different DMs with a different background, experience may produce different evaluations. In addition, different weights methods may yield different set of weights and ranking on the same problem. Based on the literature, there is no specific framework available to help DMs for selecting the best method to assign weights of criteria. A decision framework for selecting optimal weighting method is required especially subjective methods to assist DMs in making rational choice from several feasible strategies.

Different criteria values obtained from different subjective methods, and different groups of evaluators will affect the evaluation and yield different sets of criteria weights on the same problem. A decision framework for selecting the optimal subjective weighting method is needed to determine criteria weights to aid DMs in choosing more suitable weighting method for solving MCDM problems. This decision would involve several subjective weighting methods, and the decision framework to be developed would guide the DMs how to select the optimal weighting methods. A decision framework is developed by comparison among several subjective weighting methods would be a big help for the DMs to select the most accurate weights methods in decision-making process during the evaluation phase in MCDM problems.

Moreover, the Pairwise Comparisons (PCs) technique used in Analytic Hierarchy Process (AHP) method is one of subjective weighting methods, and it has inconsistency problems (Siraj, 2015; Wang et al., 2009). In inconsistency cases, the researchers need to revise judgments by DMs to get new judgments on the criteria, and this process may be repeated several times. Therefore, there are difficulties encountered by some researchers when the judgments are inconsistent, especially when there is a significant number of criteria or alternatives. For instance, in PCs method, the number of comparisons is increasing as the number of criteria increases. Therefore, a large number of criteria may lead to inconsistent judgments, and these judgments may need to be revised by DM several times. This issue needs to be addressed by proposing a method that can overcome the inconsistency without revising from DMs.

Regarding the e-learning approaches, there is still a few quantitative researches particularly on the evaluation of criteria towards the implementation of e-learning approaches in higher education. Therefore, there is a gap in past studies due to lack of quantitative evaluation research for integrating e-learning in teaching and learning process in higher education. Hence, because of the flexible nature of e-learning approaches and its increasing demand day by day, there is a real need to evaluate e-learning approaches in higher education by experts in this field.

1.3 Research Questions

- I. How to address inconsistency problem in pairwise comparisons technique?
- II. How would criteria weights about the e-learning approaches be prioritized?
- III. How various weighting methods influence the outcomes of the evaluation of the e-learning approaches?
- IV. What is the suitable approach of e-learning to be applied in the selected university?

1.4 Objectives of the Study

Main objective:

To develop a decision framework on selecting the optimal subjective weighting method for evaluating e-learning approaches.

Specific objectives:

- I. To propose a new procedure to overcome the inconsistency problem in pairwise comparisons technique.

- II. To develop a decision framework on selecting the optimal subjective weighting method.
- III. To validate the framework in evaluating e-learning approaches as a case-study in a selected public university.

1.5 Significance of the Study

This study derives its importance from the following:

- I. Providing a procedure to overcome the inconsistency problem in pairwise comparisons method.
- II. Providing a framework to decide the optimal subjective weighting method in solving MCDM problem.
- III. Demonstrating the application of the framework in a case study on evaluating e-learning approaches.

1.6 Scope of the Study

In general, this research concentrated on subjective weighting methods to determine the importance of multiple criteria in MCDM methods. In particular, this study focused on the weighting methods which used to solve MCDM problems related to e-learning approaches. Nine subjective weighting methods were used for analysing e-learning criteria weights namely: RM, ROC, RE, RR, RS, RW, GW, DPA, and PCs. The data were collected from selected respondents in Universiti Utara Malaysia (UUM) through questionnaires in 2016. The questionnaires consisted of the importance of e-learning approaches and essential criteria involved in decision making.

The participants were from management staff (administrative) in the university, academic staff and postgraduate students who interested in e-learning. The data have been used to assess e-learning approaches via comparison of nine subjective weighting methods, and select the best criteria weights for evaluating e-learning criteria. Based on best criteria weights, TOPSIS technique was used to choose the most suitable approach of e-learning in the chosen university. Five e-learning approaches were evaluated to select the best e-learning approach namely: ICT supported face-to-face learning, flipped classroom, blended learning, synchronous learning and asynchronous learning.

1.7 Research Organization

The organization of this research is as follows: Chapter One presents an overview of this research. It contains a brief introduction and background of the study, the problem of the study, research questions, research objectives, significance of the study, the scope of the study and research organization. An overview of MCDM techniques, and weighting methods is presented in Chapter Two. Chapter Three presents an overview of e-learning. The methodology in conducting this study is explained in Chapter Four. The proposed TROI method is presented in Chapter Five. Then, the results and discussion displayed in Chapter Six. Finally, Chapter Seven included conclusions and recommendations.

CHAPTER TWO

AN OVERVIEW OF MULTI-CRITERIA DECISION MAKING

2.1 Introduction

There are two major parts in this chapter as clarified in Chapter One. The initial part includes a description of various sorts of MCDM approaches in various fields, as well as a description of some MCDM methods with their advantages and disadvantages. The second part describes multiple kinds of weighting methods and a summary of some benefits and disadvantages of these methods. The summary and discussion is presented at the end of this chapter.

2.2 Multi-Criteria Decision Making (MCDM)

MCDM has seen a remarkable quantity of usage during the last several years. Its function has risen considerably in various application areas since there are new approaches and improvement to the old procedures.

2.2.1 Decision-Making Process in MCDM

Decisions-Making is a cognitive procedure of ranking available alternatives to select the most preferable (Siraj, Mikhailov, & Keane, 2012). Wallenius et al. (2008) mentioned that the MCDM describes making judgments in the existence of a number of criteria and is considered to be an active area of research. Simon (1960) clarified that the MCDM includes a series of steps: the definition of the problem, constructing the preferences, assessing the alternatives, and identifying the best choices. However, it may be difficult to obtain one best answer, especially when the decision relies on several objectives. Throughout the last few years, a variety of mathematical

techniques has been established for choosing the most suitable alternatives. This is due to the fact that traditional single criteria decision-making methods could not deal with the intricacy of present systems and this issue (San Cristóbal, 2011).

According to Hwang and Masud (1979), the MCDM problems involve the selection of one of the 'best' alternatives from a pool of chosen alternatives described in terms of their attributes. Tzeng and Huang (2011) stated that when considering single attribute problems decision-making is extremely intuitive since we only need to select the alternative with the higher preference rating than the other. However, when Decision-Maker (DM) evaluates alternatives with multi-criteria, many problems, such as weights of attributes, conflicts among criteria, and preference dependence, seems to complicate the problems and needs to be processed by more sophisticated methods. In order to deal with MCDM problems, Tzeng and Huang (2011) illustrated some steps as follows:

Step 1: Identifying the problems. Figuring out the number of criteria and alternatives and understand the way of the problems.

Step 2: Constructing the preferences. Gathering the appropriate information about constructing preferences from DMs.

Step 3: Evaluating the alternatives. Additional work builds a set of possible choices to ensure that the objective will be achieved.

Step 4: Finding and identifying the most effective alternative. This is to choose a suitable way to assist us assess and enhance the possible alternatives.

In general, all the MCDM methods take the steps described by Yoe (2002) as shown in Figure 2.1 below.

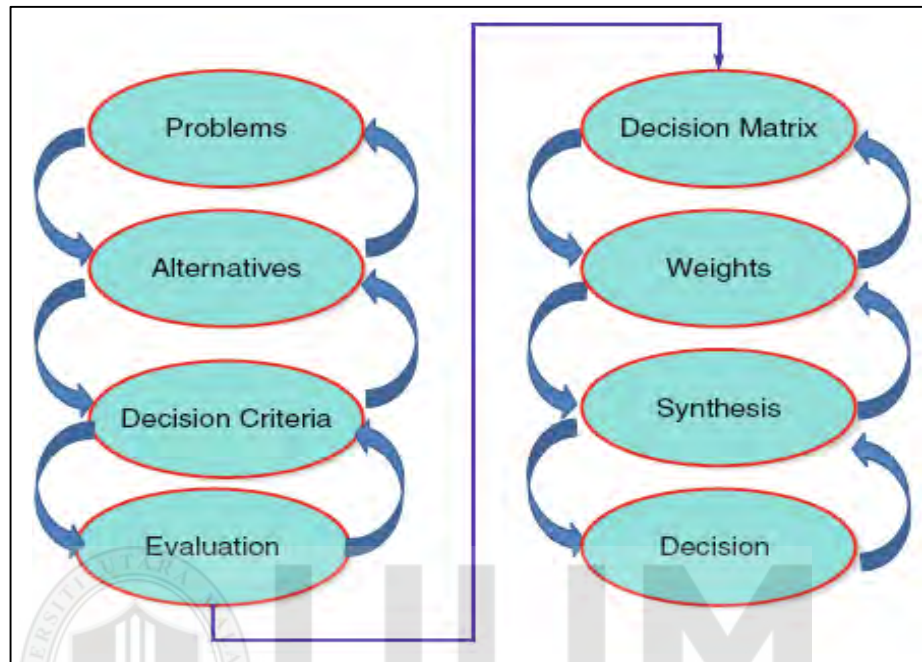


Figure 2.1. Steps in decision-making of MCDM techniques

The decision-making process in MCDM techniques typically circulations from top to bottom as shown in Figure 2.1. However, it may have to go back to any one of the prior actions if different or new details were discovered at the later time. The steps of MCDM methods described as follows:

- I. Specify multi-criteria problems as well as objectives.
- II. Define alternatives (options) for meeting goals (alternatives).
- III. Define attributes (criteria) to determine the performance of goals.
- IV. Perform studies to collect statistics or data and assess attributes.
- V. Formulate a decision matrix by organizing criteria versus alternatives.
- VI. Calculate criteria weights whether objective or subjective.

VII. Rank alternatives.

2.2.2 MCDM Definition

The International Society on MCDM defines it as the study of approaches and processes by which multiple and contradictory attributes could be integrated to make an acceptable decision (Kou, Miettinen, & Shi, 2011). Roy (1996) defines MCDM as “being a scenario in which, having specified a set A of activities and a family F of criteria. The decision maker desires; to identify a part of activities considered to be the most effective with respect to F (choice problem); to divide A into parts (subsets) according to some standards (sorting problem); to place (rank) the activities of A from the most effective to worst (ranking problem); to define activities and their effects in a formalized and methodical manner, so that decision-makers can assess those activities (description of problem)” (Schramm & Morais, 2013). In the literature available, many terms have been used for MCDM such as Multi-Criteria Decision-Analysis (MCDA), Multi-Objective Decision-Making (MODM), Multi-Attributes Decision-Making (MADM), and Multi-Dimensions Decision-Making (MDDM).

In MODM, the decision problem is identified by the presence of multiple objectives that need to be optimized versus a set of possible and available constraints (Diakaki et al., 2010). While the assessment in MADM is a set of choices versus a set of attributes. Wang et al. (2010) stated that the MADM is one of the most preferred MCDM techniques to be certified to address issues related to various perspectives. MCDM techniques focus on enhancing the quality of decisions by making the procedure more clear, logical, and reliable. Lots of books, thousands of applications,

software packages, dedicated scientific journals, and university programs are available on MCDM approaches (Figueira, Mousseau, & Roy, 2005).

2.2.3 Classification of MCDM Methods

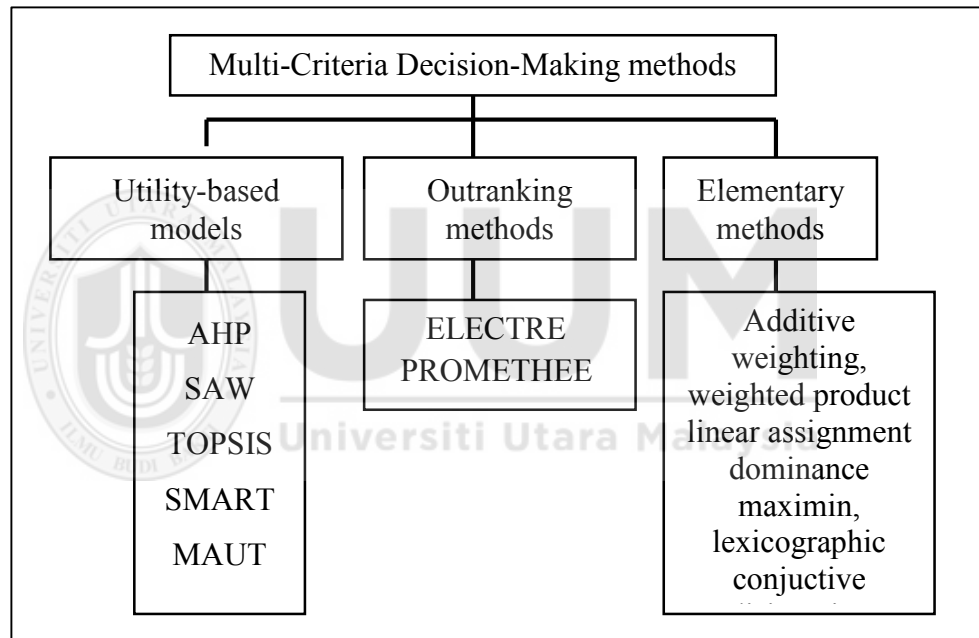
In the literature, there are lots of discussions regarding which technique of MCDM is the best to be used in solving problems. The MCDM is usually used to choose the most accurate solution based on multi-criteria and distinctive alternatives (Greening & Bernow, 2004). Several classifications and categorizations exist for the different types of MCDM methods. Hwang and Yoon (1981) classified various MCDM approaches based on diverse kinds of data whether on attributes or alternatives. Hajkowicz, McDonald, and Smith (2000) presented classification based on qualitative or quantitative information or both (input data).

However, Schramm and Morais (2012) found a more popular way, where the objective is to bring MCDM techniques with each other according to some resemblances, and this is done by dividing MCDM methods into three categories. The categorization of the MCDM approaches made according to the sort of input information, and the adapted way of evaluation or analysis (Greening & Bernow, 2004). Roy (1990) classifies MCDM (see Figure 2.2) as follows:

- I. Utility-based models based on unique synthesis criterion approach, eliminating any incomparability. Utility-based models namely: AHP, SAW, TOPSIS, SMART, and MAUT.
- II. Outranking methods based on outranking synthesis approach, accepting incomparability. These consist of the development of a relationship which

represents the DM's preferences, to help the DMs solve their problems through relationship being explored. Outranking methods such as: ELECTRE and PROMETHEE.

- III. Elementary methods based on interactive local judgment way, with trial-error interaction. Elementary methods namely: Additive weighting, weighted product, linear assignment, dominance, maximin, lexicographic, conjunctive, and disjunctive.



*Figure 2.2.*Classification of MCDM methods

It is noted that not all techniques of MCDM are suggested for addressing any problem in multi-criteria. It depends on the data collection regarding the issue, whether the information on criteria or alternative is quantitative (judgments by DM) or qualitative (initial data). The sort of available data will mainly identify the technique of MCDM to be utilized for solving a specific issue of multi-criteria (Zardari et al., 2015).

2.2.4 MCDM Prioritization Methods

There exist numerous MCDM strategies to aid a DM in prioritizing alternatives. As one would expect, various MCDM methods may produce various results for the same problem. Siraj (2011) stated that the prioritization approaches in MCDM typically are two types, i.e., outranking and compensation techniques. The outranking approaches are based on multiple comparisons in between alternatives that typically lead to an ordinal ranking rather than finding a global utility. On the other hand, the compensation approaches compute aggregated performance value (or utility) for each alternative (single dimensional problems). The following sections will briefly discuss the widely used MCDM methods.

2.2.4.1 Weighted Sum Model (WSM)

The WSM method is probably one of the most commonly used compensation approaches. If there are n criteria and m alternatives then, the best alternative is the one that in the maximization case, as the following expression in Equation (2.1) (Fishburn, 1967):

$$A_{WSM-score}^* = \max_i \sum_{j=1}^n a_{ij} w_j, \quad \text{for } i = 1, 2, \dots, m \quad (2.1)$$

The maximum score for alternative A_i^* is considered to be the most suitable. All the criteria in WSM method as benefit criteria implying that the feasibility of each alternative increases with its value. This method has intuitive to DMs, ability to compensate among criteria, computation is easy does not need complicated computer programs (Velasquez & Hester, 2013).

2.2.4.2 Weighted Product Model (WPM)

The WPM is similar to WSM, where multiplication is utilized to aggregate outcomes. The criteria in WPM model also as benefit criteria (compensation approach). The main distinction with WSM is that there is multiplication rather than addition in the model as shown in Equation (2.2). Triantaphyllou (2000) explained that:

“Each alternative is compared with the others by multiplying the number of ratios, one for each criterion. Each ratio is raised to the power equivalent to the relative weight of the corresponding criterion. In general, in order to compare two alternatives A_K and A_L , the following product has to be calculated” (p. 8).

$$R\left(\frac{A_K}{A_L}\right) = \prod_{j=1}^n \left(\frac{a_{Kj}}{a_{Lj}}\right)^{w_j}, \text{ for } K, L = 1, 2, \dots, m \quad (2.2)$$

2.2.4.3 Multi-Attribute Utility Theory (MAUT)

MAUT method is one of the most popular (compensation approach) MCDM techniques (Fishburn, 1967; Keeney, 1977). This approach relies on the preference of the DM to identify the utility function which is specified over a set of criteria, where the utility of each criterion or attribute does not need to be linear (Keeney & Raiffa, 1993). Konidari and Mavrakakis (2007) stated that MAUT is an anticipated utility theory that can determine the most effective strategy in a provided problem by allocating a utility to each possible consequence and computing the best utility. This method has two main disadvantages; it needs a lot of input, as well as preferences, needs to be precise (Velasquez & Hester, 2013). Sarkis and Sundarraj (2000) have described the basic steps of MAUT as:

- I. Identifying fundamental objectives, sub-objectives, and their attributes.
- II. Evaluation of attribute's scores and weights.
- III. Finding the best suitable choice by using weights and scores to determine overall utility.
- IV. Sensitivity analysis to survey how a change in a criterion's weight influences the overall utility.

2.2.4.4 Analytic Hierarchy Process (AHP)

AHP is a commonly utilized technique for dealing with decision-making issues. In AHP, the problem is constructed as a hierarchy-breaking down the decision from top to bottom. The main characteristic of this technique is the use of pairwise comparisons (outranking method), to compare the alternatives on the different attributes and to assess attributes weights (Løken, 2007). Saaty (1980) has developed the AHP in the theory of prioritized hierarchies. Thus, it became common and has been used broadly to model problems in many application areas. AHP used to rank, select and assess based on a wide variety of decision alternatives.

The extreme exclusiveness of AHP is its inherent ability to weight a significant number of various factors, of different natures, containing both quantitative and qualitative data, to make a decision rely upon a formal and numerical process (Liberatore & Nydick, 2008). According to Salmeron and Herrero (2005), AHP technique uses the principle of Pairwise Comparisons (PCs). Creating PCs seem to be a more reliable manner of getting the real weights than getting them directly. This method is easier to assess the relative weights of each attribute on the others. Vaidya and Kumar (2006), mentioned that AHP method is also a flexible way in that it can

be integrated with other procedures such as quality function deployment, linear programming, fuzzy logic, etc. Douligieris and Pereira (1992), suggested that four steps are involved in AHP procedure.

Step 1: Decompose problem into a hierarchy of more general sub-problems.

Step 2: Gather trade-off information input by pairwise comparisons of decision elements.

Step 3: Use the ‘Eigenvalue’ method to assess the relative weight of the hierarchy attributes.

Step 4: Collection of attributes is made via a mixture of relative weights so regarding make a comprehensive assessment of all alternatives.

The AHP technique has some considerable benefits. For instance, it is a relatively simple manner for DMs. The main advantage of the use this technique is to convert both subjective and objective judgments into relative weights of importance. Contrast, the connection between attributes and options could cause inconsistencies judgments (Velasquez & Hester, 2013).

2.2.4.5 Analytic Network Process (ANP)

The ANP was proposed by Saaty (1996) which is a general form of the AHP method to release the restrictions of the hierarchical structure, and it is more concentrated with network structure. The fundamental structure is an influence network of clusters and nodes consisted of within the clusters. By raising the super-matrix into the

limiting powers, the global priority vectors can be gotten with the specific network structure for identifying dependence and feedback problems among criteria (Saaty, 1996). However, the main disadvantage is that it disregards the various impacts among clusters as it is nonlinear (Wang, Lee, & Wu, 2007).

2.2.4.6 Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) Method

The PROMETHEE was proposed by Vincke and Brans (1985) to solve the multi-criteria problems. This technique is identified by simplicity of use and reduced intricacy. The PROMETHEE utilizes the outranking methodology to perform pairwise comparisons of alternatives to rank them on some criteria.

According to Figueira et al. (2005), The PROMETHEE I and PROMETHEE II have been developed by Brans and presented for the first time in 1982. A few years later Brans and Mareschal developed PROMETHEE III and PROMETHEE IV. In 1992 and 1994, Brans and Mareschal further suggested two nice extensions: PROMETHEE V and PROMETHEE VI. The key advantages of these methods are that it does not require the hypothesis that the attributes are proportional. Nevertheless, it does not give a comprehensible method of allocating weights.

2.2.4.7 Elimination and Choice Translating Reality (ELECTRE)

The ELECTRE method is a family of outranking approaches. This technique is capable of handling discrete attributes that are both qualitative and quantitative in nature and gives complete ordering of the alternatives. The analysis is focused on the dominant relations among alternatives. This is done by taking two sets of

comparisons to establish an outranking relation from the choices available (Figueira et al., 2005). The DM can support for various decisions that there is indifference among the alternatives, strong, weak, or equal preference (Milani, Shanian, & El-Lahham, 2006).

Similar to PROMETHEE, ELECTRE method also has a significant number of variations: ELECTRE I, ELECTRE II, III, and IV (Milani et al., 2006). According to Velasquez and Hester (2013) the ELECTRE method takes into account uncertainty and vagueness, this is the main advantage of this approach, but the procedure and consequences may be difficult in layman's terms.

2.2.4.8 Technique for Order Preference by Similarity to Ideal Solutions (TOPSIS) Method

The TOPSIS was presented by Hwang and Yoon (1981) to allocate the preferred option that relies on the ideas of the compromise or concession solution. In fact, the compromise could be considered as selecting the settlement with the shortest distance from the ideal solution and the farthest distance from the negative ideal solution (Hwang & Yoon, 1981). According to Triantaphyllou (2000), The TOPSIS method assumes that each criterion has a tendency of monotonically increasing or decreasing. The Euclidean distance approach was proposed to evaluate the relative closeness of the alternatives to the ideal solution. Unlike ELECTRE, TOPSIS is a compensation technique and can generate global weights. This approach starts with the weighted normalization of all performance values against each criterion.

Velasquez and Hester (2013) stated that the method has a simple process, as well as the number of steps remains the same regardless of the number of attributes. On the other hand, it does not consider the connection of criteria.

2.2.5 Selection of an Appropriate MCDM Method

Triantaphyllou (2000), in a comparison of techniques commonly used in MCDM, concluded that discovering the best technique may be impossible. Abrishamchi, Ebrahimian, Tajrishi, and Mariño (2005) mentioned that there is no technique can give ideal outcomes, as well as choosing a best MCDM technique is once again a multi-criteria problem itself. Guitouni and Martel (1998) argued that various techniques yield various suggestions in MCDM problems.

2.2.6 Advantages and Disadvantages of MCDM Techniques

Numerous MCDM methods have been created and utilized over the last several decades. Velasquez and Hester (2013) stated that based on the literature, the benefits and disadvantages of some MCDM techniques are summarized in Table 2.1.

Table 2.1

Advantages and Disadvantages of MCDM Techniques

Techniques	Advantages	Disadvantages
MAUT	Takes uncertainty into account; can incorporate preferences.	Needs a lot of input; preferences need to be precise.

Table 2.1. *Continued*

AHP	Easy to use; scalable; hierarchy structure can easily adjust to fit many sized problems; not data intensive”.	“Problems due to interdependence between criteria and alternatives; can lead to inconsistencies between judgment and ranking criteria; rank reversal.
ELECTRE	Takes uncertainty and vagueness into account.	Its process and outcome can be difficult to explain in layman’s terms; outranking causes the strengths and weaknesses of the alternatives to not be directly identified.
PROMETHEE	Easy to use; does not require assumption that criteria are proportionate.	Does not provide a clear method by which to assign weights.
TOPSIS	Has a simple process; easy to use and program; the number of steps remains the same regardless of the number of attributes.	Its use of Euclidean Distance does not consider the correlation of attributes; difficult to weight and keep consistency of judgment.

Source: Velasquez and Hester (2013, p63).

Outranking approaches, which prevailed early on in the advancement of the MCDM area like PROMETHEE and ELECTRE, were surpassed by the use of value measurement methods like MAUT, AHP and ANP. These techniques, could be incredibly effective in their applications, if assessed properly. TOPSIS technique is a compensation approach, and the DM can assign weight directly when he or she evaluate criteria or alternatives. For that, TOPSIS technique was a suitable method in this research to evaluate e-learning approaches.

2.3 Weighting Methods

Multi-Criteria problems include criteria of differing importance to DMs. Then, details regarding the relative importance of the criteria are needed, and this typically realized by assigning a weight to each criterion. Therefore, the derivation of weights is the main step in generating the DM's preferences. For that, a weight can be defined as a value allocated to an assessment criterion that shows its importance about other criteria (Malczewski, 1999). Therefore, the weights for criteria reflecting or describing their relative importance, and the weights are typically normalized to sum to one (Brans & De Smet, 2016; Schoner & Wedley, 1989).

In MCDM methods use attributes weights in their aggregation procedure. Criteria weights play a vital role to measure preferences of alternatives. The MCDM approach uses these weights in various techniques. Therefore, it has developed different methods to be employed in MCDM processes. Choo, Schoner, and Wedley (1999) recommended that the questions presented to the DM need to convey the appropriate definition of attribute weights, as well as the questions presented to the DM, should be simple and direct without compromising the underlying theoretical validity. The weights designated to attributes in the multi-criteria evaluation process is an essential step for solving MCDM problems. Tervonen, Figueira, Lahdelma, Dias, and Salminen (2009), stated that in an MCDM method giving the weights to criteria is the difficult mission. The core purpose of a weights technique is to assign ordinal and cardinal values to various attributes to show their relative importance in MCDM technique.

2.3.1 Classification of Weights Approaches

In literature, various weights methods were proposed to allocate weights to the attributes. The ‘equal weights method’ is the simplest method to determine weights to the attributes that the weights distributed equally among all the attributes (Wang, Jing, Zhang, & Zhao, 2009). The weighting methods classified by Wang et al. (2009) into three categories: “subjective, objective, and combination (integrated) weighting methods”. Assigning weights to the attributes in subjective weighting methods is based on the preferences of the DM. While assigning weights to the attributes in objective weighting methods is based on the analysis of initial data.

In subjective weighting methods, the weights are derived directly from the DMs’ judgments on attributes. Here, assign weights is only according to the preferences of DM. Ahn, (2011) stated that the DM can influence analytical outcomes of alternatives based on the weighting due to DM level of experience and knowledge in the relevant field. On the other hand, the objective weighting methods assign attributes weights by solving mathematical models automatically without needing DM’s preferences (Aalianvari, Katibeh, & Sharifzadeh, 2012).

2.3.2 Subjective Weights Methods

The previous studies have shown several subjective weights methods in order to calculate criteria weights. The methods are to be discussed briefly in the next subsection.

2.3.2.1 Rating Weights Method (RM)

The RM gets a score from a DM to represent the importance of each attribute. Nijkamp, Rietveld, and Voogd (1990) mentioned that the scales 1 – 5, 1 – 7 or 1 – 10 indicate the importance of attributes. The RM is possible to modify the importance of one attribute without adjusting to the weight of another (Hajkowicz et al., 2000). In the RM procedure, the value for each criterion is divided with the least important criterion. Let w_j be a weight for criterion j , $j = 1, \dots, n$. Let w^* be the weight for the least important criterion. So the raw weight for criterion j is w_j/w^* , and then the final weight is found by normalizing the weight. The easiest way to normalize the weight is by taking the raw weight for the selected criteria and divide it by the sum of all raw weights (Kumar, Pravesh, & Tripathi, 2015). This normalization process will ensure that the sum of weights is one.

2.3.2.2 Direct Point Allocation Weights Method (DPA)

In Direct Point Allocation weighting process (DPA), the DM has a ‘budget’ of points to assign the attributes directly to reflect their relative importance. In this method, the total weights of all criteria must be sum up to 100. Clearly, in DPA there is no need to normalize the weights since the sum of 100 is already prescribed (Roberts & Goodwin, 2002). In DPA method, the decision not to give any direction on what numbers to use was ready on purpose to see how the DMs choose the numbers without a given reference and the ranges of attributes were described to the subjects (Pöyhönen & Härmäläinen, 2001). Determining weights by DPA may produce various profiles of decision weights, and the result is sometimes quite surprising (Jia, Fischer, & Dyer, 1998).

2.3.2.3 Ratio Weighting (RW) Method

The RW requires the DMs to rank the related attributes based on their importance (Edwards, 1977). In RW, DM should allocate ten for the least important attribute, and the rest of attributes are judged as multiples of ten. The weight of a criterion is obtained by dividing the criterion's weight with the sum of all attributes' weights. The RW method has a significant advantage of being easily taught for DM, but if it consists of too many criteria, the results may not be accurate. The RW is regarded as an algebraic, direct procedure and decomposed (Edwards, 1977).

2.3.2.4 Ranking Methods

The ranking methods are one of the important and easier ways to allocate weights to the attributes. In ranking methods, there are four main techniques to compute weights of criteria namely: rank reciprocal, rank sum, rank exponent and rank-order centroid. In the ranking, each criterion under consideration is ranked in order of the DMs preference from the most to the least important, the most important = 1, next important = 2, and so on (Kumar et al., 2015).

The DM chooses and ranks from a set of n criteria, providing every criterion j a rank r_j , $r_j = 1, 2, \dots, n$, the rank for each criterion is inversely linked to weight, that is, if $r_j = 1$, this means that criterion j is with the highest weight value, while if rank $r_j = n$, then criterion j will have the lowest weight (Roszkowska, 2013).

Overall, ranking methods are simple ways of giving weights to criteria according to their relative importance, but may be difficult with a large number of options to

determine weights because the respondent will lose his overview (Chang, Yang, Goodrich, & Daranpob, 2010; Hajkowicz et al., 2000; Nijkamp et al., 1990).

2.3.2.5 Trade-Off Weights Method

The Trade-Off weights method uses direct evaluation of Trade-Off procedures that the DM is willing to make a comparison between pairs of alternatives (Hobbs, 1980; Rowe & Pierce, 1982). The Trade-Offs term is a unique set of weights which allow all of the equally chosen options in the trade-offs to obtain the same overall value. The Trade-Off approach requires the DM to compare between two alternatives with relation to two criteria at a time and evaluate which one of the alternatives is preferred, and by asking for many assessments, one can infer how much weight the DM has given to the several attributes (Kumar et al., 2015). The Trade-Off analysis method involves the assessment of indifferent points between two options on attributes at a time.

Furthermore, indifference Trade-Off interpretation (Choo et al., 1999) is used in interactive compensatory approaches (Stewart, 1992) to estimate the attributes weights $w_1, \dots, w_n$. The ratio w_i/w_j denoted as answers to compensate for the unit loss in C_i . In practice, with all scores in other attributes held constant, to approximate the Trade-Offs w_i/w_j , DM is asked to determine the compensation of one attribute on another. Its advantage is the strong theoretical foundation, but it is time-consuming to elicit weights compared with the other ways (Chang et al., 2010).

2.3.2.6 Fixed Point Scoring Weights Method

Hajkowicz et al. (2000) have mentioned that the DM is needed to organizing a specific number of points for the features (attributes) in the Fixed Scoring weights approach, and the highest scores of points represent that this attribute has a significant importance. Many DMs are very informal to use this method with percentages as a measure. The main advantage of this method that it is influenced DMs to use a Trade-Off for problems that are required decisions. However, this shows that the DM has a difficult duty that needs a specific consideration to distribute the importance that related to each attribute.

2.3.2.7 Graphical Weighting (GW) Method

The GW technique has required a DM to place a mark on a horizontal line (9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9). That means, the criterion is either more, equally or less important than another criterion by a factor of 1 – 9, and then build the decision matrix as in PCs. Therefore, a quantitative weight for a criterion can be calculated by taking the sum of each row and then normalized scores to obtain an overall weights vectors. The GW method enables DMs to express of preferences in a purely visual way (Hajkowicz et al., 2000). However, GW is sometimes criticized, since it allows DMs to assign weights in a more comfortable way. For instance, to select the important one of two criteria, it will be easy for DM to compare between them by marking on the horizontal line without considering any implications of attributes weights, and also they have no time for more complicated and involved approaches (Zardari et al., 2015).

2.3.2.8 SIMOS Method

The principal development in this technique suggested by Simos (1990) includes associating a “playing card” with each attribute. The participants in the evaluation process are asked to place the cards (or attributes) from the minimum into the maximum based on their importance. To allow participants to reveal a vigorous preference among attributes, another set (white colour) of cards is presented. Thus, the participants are asked to present white colour cards between two successive coloured cards, while the number of white colour cards is proportional to the distinction between the importances of the considered attributes. Afterward, calculating the weights of criteria will be through dividing the rank positions on the sum of the criteria positions (Wang, 2009).

2.3.2.9 Swing Weighting Method

The swing process begins from an alternative with the worst consequences on all attributes (Von Winterfeldt & Edwards, 1986). The procedure in swing method allows DM to change one of the attributes from the worst consequence to the best. This method requires DM to choose the attribute that he/she would most prefer to modify from its worst to its best level, the attribute with the most chosen is most important, and to allocate 100 points to the most important attribute. Afterward, the DM is continued to select the attributes to change from the worst level to the best which he/she considers to be the second most desirable advancement and to allocate points less than 100 to that attributes change. Finally, the derived percentages in this approach are normalized from the raw weights to get the attributes weights (Wang, 2009). Swing method's strength is that it is straightforward manner and a

comparatively simple, but it does not allow DMs to compare every attribute with each other directly (Zardari et al., 2015).

2.3.2.10 Delphi Method

Historically, the Delphi technique has been used to quantify expert judgment. The Delphi method was illustrated as early as 1925 by Whitehead in the text 'Science and the Modern World' (Goodman, 1987). This strategy was used as a first time via the Rand Corporation 1950s in group decision-making. Dalkey and Helmer (1963) utilized the strategy to develop group agreement of opinions on plan decisions without having the group meet in commission format to avoid the negative impact from a face-to-face decision-making procedure. The use of Delphi technique aims to get evaluated judgments from experts in a certain topic area, using frequent questionnaires in a systematic and unbiased manner (Chang, Hsu, Williams, & Pan, 2008). Each panellist remains nameless to the others, therefore decreasing the risk of personal effects as well as individual bias. Thus, panellists can change their answers to the questions, once confronted with the outcomes from the previous round. The aim of this procedure is to get a consensus of opinions on the direction and extent of the impacts inside the panel of experts (Still, May, & Bristow, 1999).

Nevertheless, it caused some restrictions containing the potential of falling victim to the bandwagon issue. Other weaknesses felt by person-to-person meetings, such as tracing a single opinion, becoming side-tracked, and losing sight of the end of the treatment. Four characteristics that eliminate such problems and characterize the Delphi method are anonymous, iteration, controlled feedback and statistical group response (Geist, 2010).

2.3.2.11 Simple Multi-Attribute Rating Technique (SMART)

The SMART weights method was initially described as the entire procedure of rating alternatives and weights of attributes by Edwards (1977). Chen, Okudan, and Riley (2010) suggested that the SMART method is one of the simplest forms of MAUT, which requires two assumptions: preferential independence and utility independence. This method converts important weights into real numbers. The participants are asked to classify the significance of the variations in the attributes from the worst to the best attributes levels. Then they allocate 10 points to the lowest significance attributes (without explicit upper limit), and rising points are allocated to the other attributes to show their relative importance with the lowest importance attributes. Then, to calculate the final weights in this methods, the normalized weights should be estimated.

The SMART method can be utilized to get a total weighted score rapidly. Moreover, when new alternatives are added, there is no changing of the decision compared with the original value of alternatives, but it ignores the interrelationships between parameters, and also with a large number of attributes, it would be too difficult to implement (Huang, 2011). Edwards and Barron listed the deficiencies in this technique and emphasized that the weights should be more clearly interrelated to the criteria ranges (Edwards & Barron, 1994).

According to Velasquez and Hester (2013), the key advantages of SMART method allows for any weight allocation procedures, and it is easy and simple to use. Therefore, it requires less effort than MAUT method for DMs. Moreover, it also handles data well under each attribute. Despite these advantages, the process for

allocation work is not convenient considering the complicated framework (Velasquez & Hester, 2013).

2.3.2.12 Pairwise Comparisons (PCs) Method

Thurstone (1927) introduced this scientific technique as the law of comparative judgment. A DM uses PCs when he or she is unable to allocate criteria weights to the available alternatives directly. Also, the use of PCs is a vital role of the prioritization procedure in AHP, and AHP was proposed by Saaty (Saaty, 1980), which provides a rational framework for organizing a decision problem. The pairwise judgments in this technique are structured in a PC matrix, and a prioritization procedure is implemented to draw a corresponding priority vector. Thus, if the judgments are consistent, all prioritization procedures give the same results. At the same time, if the judgments are inconsistent, prioritization procedures provide different priority vectors (Saaty, 1987).

The PCs technique is an essential stage in AHP to be completed by the DMs. Nevertheless, there are some criticism of the AHP because of the some tedious procedures, particularly when there is a significant number of attributes or options. The process in PCs with the large number of criteria may leads to loss some of concentrating through evaluation process by DMs. In addition, the DMs are expected to feel exhausted and lose persistence throughout this process. In the consistency judgments, there are two types of consistency: ordinal and cardinal.

Kendall (1955) presented a measurement of ordinal inconsistency for PCs through an ordinal coefficient with no preference equivalencies among criteria. Furthermore, Jensen and Hicks (1993) improved Kendall's measurement and proposed an ordinal

consistency index, as well as they suggested the use of their proposed way in AHP. They also recommended that the proposed method (ordinal indexes) could not disregard the requirement for cardinal consistency measures in the AHP technique.

The AHP technique does not need an ordinal consistency (transitivity) of DM's judgments. The cardinal inconsistency is measured of the judgments by Saaty's CR index but does not consider their ordinal inconsistency. The cardinal inconsistency does not implies ordinal inconsistency, and vice versa. Generally, if the PC matrix is ordinal inconsistent, the value of CR is greater than 10%. Consequently, the AHP technique unconditionally assumes that satisfying the CR test may considerably decrease the possibilities of ordinal inconsistency. However, there are examples in the literature where matrices that satisfy the CR criterion can also be ordinarily inconsistent (Jensen & Hicks, 1993; Kwiesielewicz & van Uden, 2004).

The issue of improving consistency in PCs judgments has been widely debated and is still considered to be an active area for further investigation (Bakar, 2016; Bozóki, Fülöp, & Poesz, 2011; Brunelli, 2016; Ergu, Kou, Peng, & Shi, 2011; Koczkodaj, Kosiek, Szybowski, & Xu, 2015). The issue of improving ordinal consistency has been presented in companion work (Siraj, Mikhailov, & Keane, 2012). There are several methods that improve this consistency (Lamata & Peláez, 2002; Saaty, 2003) and others that complete missing values in pairwise matrices (Harker, 1987a; Shiraishi, Obata, & Daigo, 1998).

Some researchers tried to get consistent judgments based on the comparisons between the criteria in PCs method through some proposed procedures. For instance, Obata, Shiraishi, Daigo, and Nakajima (1999) and Lamata and Peláez (2002) have

employed inconsistent judgments to estimate missing comparisons. Harker (1987) proposed a procedure to derive ratings of alternatives from incomplete preferences. Xu and Xia (2014), and Zeshui and Cuiping (1999) introduced a procedure to improve the consistency of PCs method.

Overall, the issue of inconsistency in PCs has been discussed by several authors e.g. (Bozókí & Rapcsák, 2008; Koczkodaj & Szwarc, 2014; Laininen & Hämäläinen, 2003; Ramanathan & Ramanathan, 2010; Schoner & Wedley, 1989; Siraj, 2011).

2.3.3 Objective Weights Methods

The objective weights manner produces the attributes weights through the measured data and information (Wang, Jing, Zhang, Zhang, & Shi, 2008). Therefore, the literature about objective weights approaches implemented in sustainable energy and applied to other assessment systems, such as social and ecological systems (Wang et al., 2009). Following sub-sections is the brief explanation of the widely used objective weights.

2.3.3.1 Entropy Method

The Entropy is a measurement of uncertainty, as clarified by Shannon and Weaver in 1947. Deng, Yeh, and Willis (2000) stated that the entropy technique is a measurement of uncertainty in data expressed via probability theory. To compute the weights in entropy technique, the data matrix is normalized then the following Equations ((2.3), (2.4), and (2.5)) are used.

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^m x_{ij}}, i = 1, 2, \dots, m; j = 1, 2, \dots, n \quad (2.3)$$

$$E_j = -\frac{\sum_{i=1}^m p_{ij} \ln(p_{ij})}{\ln(m)} , j = 1, 2, \dots, n \quad (2.4)$$

$$w_j = \frac{1 - E_j}{\sum_{i=1}^n (1 - E_k)} , j = 1, 2, \dots, n \quad (2.5)$$

Where x_{ij} is original measured data; E_j is information entropy method; w_j entropy method weight.

The method produces more divergent coefficient values for all the attributes; it can better resolve the inherent conflict between the attributes embedded in MCDM (Diakoulaki, Mavrotas, & Papayannakis, 1995).

2.3.3.2 Criteria Importance Through Inter Criteria Correlation (CRITIC)

The CRITIC method was proposed by Diakoulaki et al. (1995). The CRITIC procedure is by use correlation analysis to discover contrasts among attributes. The vector r_j is generated where r_j means the scores of all n alternatives of the normalized matrix. Each vector r_j is characterized by the standard deviation (σ_j), which determines the quantity of the contrast intensity of the corresponding attribute.

2.3.3.3 Standard Deviation Method (SDs)

The SDs technique allocates small weights to criterion, it similar to the Entropy process that if it has similar value for criterion across alternatives. Then procedure allocates the weights of the attribute regarding their SDs via following Equations ((2.6), and (2.7)) (Jahan, Mustapha, Sapuan, Ismail, & Bahraminasab, 2012).

$$w_j = \frac{\delta_j}{\sum_{j=1}^n \delta_j} , \quad j = 1, 2, \dots, n. \quad (2.6)$$

$$\delta_j = \sqrt{\frac{\sum_{i=1}^m (x_{ij} - x_j)^2}{m}} , \quad j = 1, 2, \dots, n. \quad (2.7)$$

Where w_j is weight of criteria; δ_j is standard deviation.

2.3.4 Summary of Weighting Methods

Different weights methods yield various sets of attributes weights, and the outcomes of the MCDM methods are sensitive to attributes weights. Based on the literature reviewed, the advantages and disadvantages of subjective and objective weighting methods are summarized in Table 2.2.

Table 2.2

Advantages and Disadvantages of Weighting Methods

Techniques	Advantages	Disadvantages
Rating	Ease of usage; direct assign weight from DM.	It does not constrain DMs responses; difficult task large options.
Ranking	Simple way of giving weight; easy to follow; efficacy of selection the option.	It will be trouble with large number of criteria because the respondent will lose his overview.
Point-allocation	Easy to normalize; very well with small number.	Difficult to assign 100 point with large number of criteria.

Table 2.2. *Continued*

Ratio	It has the great advantage of being easily thought of DM.	If consist too many criteria, the result may not accurate.
Trade-off		It is time consuming to elicit weight.
Fixed Point	It is forces DMs to make a trade-off approach in decision problem; it is the most direct means of elicit weighting information from DM.	Difficult mission to evaluator which needs cautious factor to consider of the relative important of each criterion.
Graphical	It enabled DMs to express preferences in a purely visual manner.	There are several variations on the Graphical weights of attributes.
SIMOS	It verified to be effective by evaluators.	It based on unreal assumption; criteria has the same important in a not strong way.
Swing	It considers the variety of each attribute; it is a relatively simple as well as uncomplicated way.	It does not enable evaluators to compare directly each criterion with each various other.
Delphi	It avoids direct confrontation of the expert; it leads to a group decision.	It has some restriction consisting of the possibility of succumbing to the bandwagon.
SMART	Can be utilized to rapidly acquire an overall weights score; helpful when new options included.	It disregards the inter connections in between parameters with lot of attributes would be too challenging to apply.
Pire-wise	It has vital role of the prioritization procedure in AHP; it provides a rational framework for organizing a decision problem.	With large number of criteria, difficult to make acceptable judgements as consistency; difficult mission if the judgement inconsistency.
Entropy	It has been verified as adequately dependable in determining both contrast intensity and conflict of attributes.	No account of the mutual relationships among criteria; it does not give scope to designer's preference.
CRITIC	Can be easily converted into an algorithmic form.	CCSD clearer modelling mechanism than the CRITIC method.

Hobbs (1980) stated that it is imperative to emphasize the choice of weights technique for addressing an MCDM problem, and the choice of a specific way is highly reliant on the sort of problem. Hajkowicz et al. (2000) used several weights approaches (five) to assign weight into six environmental, social and economic criteria. The process of comparisons among criteria weights were made that are taken from each technique. Their outcomes show that DMs will allocate similar weight values to the attributes with the various ways. Nevertheless, small differences in weights vectors have the capability to create considerable alterations in the subsequent outcomes or ranking of options. This shows that it is undesirable to depend on any single weighting method in MCDM methods.

Moreover, there are some approaches for converting experts' judgments into relative importance for criteria. Eckenrode (1965) recommended that no considerable changes in the methods that investigated. Meanwhile, no technique is clearly superior, in any application, the preferred method relies on the intended use of the scale. Choice of weights method is important here to obtain reasonable results.

Nijkamp et al. (2013) stated several approaches to evaluating criteria weights, direct and indirect estimate. A direct estimate of attribute weight denotes to the reflecting of the relative importance of the criteria or alternatives through questionnaire surveys directly. The indirect method relies on checking out the real behaviour of respondents.

Hobbs (1980) indicated that it is extremely important to focus on the choice of weights technique for addressing MCDM problem. The criteria weights have a direct effect on the outcomes of prioritizing strategy options. Therefore, it is

important to determine the weights of the criteria rationally and truthfully (Hobbs, 1980). Table 2.3, displays several weighting methods used in different areas.

Table 2.3

Some Applications of MCDM in Past Studies

Reference	MCDM methods	Weighting methods	Area of research
Wan, Xu, and Dong (2017)	ANP, ELECTRE	2-tuple linguistic	Supply chain management
Akbari, Irawan, Jones, and Menachof (2017)	AHP	PCs	Offshore wind port
Deng (2017)	FAHP	FPCs	Supplier management
Yang, Nasr, Ong, and Nee (2017)	Fuzzy TOPSIS	TOPSIS	Designing products for remanufacturing
(Mulliner, Malys, & Maliene, 2016)	WPM, WSM, AHP, TOPSIS	WSM	Sustainable housing affordability
Wang, Zhu, and Wang (2016)	SAW, TOPSIS, GRA	SAW, TOPSIS, GRA	Experimental design
(Aghajani Mir et al., 2016)	TOPSIS, VIKOR	TOPSIS, VIKOR	Solid waste management system
(Kurilovas, Vinogradova, & Kubilinskiene, 2016)	FAHP	PCs	Learning repositories
(Arunachalam, Idapalapati, & Subbiah, 2015)	AHP, FVIKOR	Pairwise comparison, linguistic variables	Compliant polishing tool selection
(Chitsaz & Banihabib, 2015)	ELECTR III	Eigen vector	Flood management alternatives

Table 2.3. *Continued*

Lee and Seo (2015)	Fuzzy FAHP	Delphi, Pairwise comparison	Cloud service selection
Piegat and Salabun (2015)	TOPSIS, AHP	Pairwise comparison	Severity of chronic liver disease
Zardari et al. (2015)		Ranking, rating, ratio weights	Water resources management
Kumar et al. (2015)		Ranking, rating, pairwise comparison, Trade-off	Geographic information system (GIS)
Salimi and Rezaei (2015)	FAHP	Pairwise comparison	University selection
Khatwani, Anand, and Kar (2014)	FAHP, TOPSIS	Pairwise comparison	Selection an appropriate marketing channel
Erdoğan and Kaya (2014)	TOPSIS	Interval type-2 fuzzy number	Ranking private university
Van Til et al. (2014)		Ranking, rating, point allocation, pairwise comparisons	Health care
Nilashi et al. (2014)	ANP, DEMATEL	Pairwise comparisons	Construction projects
Rouyendegh and Erkan (2013)	Fuzzy ELECTRE, FAHP	Pairwise comparisons	Academic staff selection
Su, Tzeng, and Tzeng (2013)	DEMATEL, DANP	Pairwise comparisons	E-learning
Zoraghi, Amiri, Talebi, and Zowghi (2013)	FMCDM	Subjective, objective weights	Service quality in hotel industries
Syamsuddin (2012)	FAHP	Pairwise comparisons	E-learning
Dai, Fu, and Cai (2012)	Fuzzy comprehensive evaluation	Pairwise comparisons	Ecological environment quality evaluation
Schuwirth, Reichert, and Lienert (2012)	MAVT, MAUT	SWING, trade-off	Pharmaceutical removal from hospital wastewater

Table 2.3. *Continued*

(Eskandari, Homaei, & Mahmodi, 2012)	SAW	Pairwise comparisons, rank ordering method	Landfill siting
(Toosi & Samani, 2012)	AHP, SAW	Pairwise comparisons, SAW	Water pollution control
(Morais & de Almeida, 2012)	PROMETHEE II	Ranking	Water resources management
(Aalianvari et al., 2012)	AHP, Fuzzy Delphi	Delphi method. Pairwise comparisons, fuzzy weights	Potential of ground water flow
Tai, Chen, and Wang (2011)	AHP, TOPSIS	Pairwise comparisons, fuzzy linguistic	E-learning
Özcan, Çelebi, and Esnaf (2011)	TOPSIS, ELECTRE, Grey theory	SIMOS procedure	Ware house selection
(Guo & Yu, 2011)	TOPSIS, AHP	Pairwise comparisons	valuation of railway
(Afshar, Mariño, Saadatpour, & Afshar, 2011)	FMCDM based on TOPSIS	Fuzzy pairwise comparisons, UNEP,	River basin
(Kaya & Kahraman, 2011)	Fuzzy AHP, VIKOR,	Fuzzy pairwise comparisons	Selection of forested water shed
(Huang, 2011)	MAUT	SMART	Recommended system for e-Commerce
(Mutikanga, Sharma, & Vairavamoorthy, 2011)	PROMETHEE	Revised SIMOS	Water loss management
(Sadi-Nezhad, Etaati, & Makui, 2010)	FANP	Pairwise comparisons	E-learning
Chen et al. (2010)	MAUT	SMART	Construction method selection

A number of techniques are presented in Table 2.3. Its shows subjective and objective weighting methods applications along with the list of applications of various fields of research applications from 2010 to 2017. Based on the literature, different weights methods may yield different set of weights and ranking on the same

problem. In addition, there is no specific framework available to help DMs for selecting the best method to assign weights of criteria. A decision framework for selecting optimal weighting method is required especially subjective methods to assist DMs in making rational choice from several feasible strategies.

In this study, several subjective weighting methods were chosen based on their most commonly used in literature, to assign attributes weights based on the preferences of the DMs, and also proposed a new methodology on how to select the best subjective weights method for evaluating e-learning approaches.

2.3.5 Geometric Mean

The geometric mean is a type of average, which indicates the central tendency or typical value of a set of numbers by using the product of their values. The geometric mean is defined as the n th root of the product of n numbers.

A geometric mean is often used when comparing different items when each item has multiple properties that have different numeric ranges. It applies only to numbers of the same sign. It is also often used for a set of numbers whose values are meant to be multiplied together or are exponential in nature (Wei et al., 2013). The geometric mean is also one of the three classical means; arithmetic mean and the harmonic mean. The arithmetic mean is the sum of the data items divided by the number of items in the set. The harmonic mean is a very specific type of average. It's generally used when dealing with averages of units, like speed or other rates and ratios. For all positive data sets the harmonic mean is always the least of the three means, while the arithmetic mean is always the greatest of the three and the geometric mean is always in between (Kalder, 2012).

2.3.6 Summary and Discussion

This chapter starts with the discussion of the initial part of a literature review on various sorts of MCDM methods in different fields, as well as a description of some MCDM methods with their advantages and disadvantages. It explains weights methods and a description of various weights techniques with summed up benefits and disadvantages of these methods.

A major criticism of MCDM is that different techniques may yield different results when applied to the same problem. In weighting methods, also different techniques of weighting methods may give different ranking when applied to the same problem. The previous studies revealed none of best weighting method in determining the criteria weights. For that, this study proposed a decision framework to select the optimal weights method from several weighting methods for solving MCDM problems. The provision of this framework would help DMs to select the optimal subjective weighting method for solving multi-criteria problems.

Moreover, one of the subjective weighting methods that is the PCs technique used in AHP method has inconsistency problems (Bakar, 2016; Siraj, Mikhailov, & Keane, 2015). It requires the researchers to refer the DMs again in order to obtain new scores or ranks of the criteria upon inconsistency cases. So, it will be a difficult mission for the researchers if the criteria weights are inconsistency. Based on the literature, there is no method in previous studies addressed this problem without revising the judgments by DM. In addition, the main reason that leads to inconsistency problem in PCs is the number of criteria or number of comparisons among criteria. In this study, a new method has been proposed to correct judgments

in inconsistent PC matrix, as well as to reduce the number of comparisons significantly, as discussed in the next chapter.

In this study, the e-learning criteria were analysed by several subjective weighting methods. In particular, RM, ROC, RE, RR, RS, RW, GW, DPA, and PCs methods were the chosen techniques, because the methods were most commonly used in the previous studies (Zardari et al., 2015).

The following chapter focuses on e-learning regarding definition of e-learning, importance of e-learning, e-learning in Malaysia, e-learning approaches, decision making of e-learning, and criteria of e-learning.



CHAPTER THREE

AN OVERVIEW OF E-LEARNING

3.1 Introduction

This chapter consists of the different types of e-learning, decision-making process more about e-learning and also criteria of e-learning approaches. The summary and discussion is presented at the end of this chapter.

The term e-learning has only been in existence since 1999, when the word was first utilized at Computer Based Training (CBT) systems seminar in Los Angeles. Other words also began to spring up in search of an accurate description such as “online learning” and “virtual learning”. this word was meant to qualify a way to learn based on the use of new technologies allowing access to online, interactive and sometimes personalized training through the Internet or other electronic media (Nicholson, 2008).

Through the rapid development of the internet, internet users need more harnessing and enhancement of education, skills development, and training programmers. Nevertheless, e-learning has come to be one of the main domains of discussion in the educational profession (Khan, 2005). E-learning will not just be presenting new technology for teaching and learning, but e-learning will also present a new procedure of learning that requires special specifications like the preparing and training of the academic staff in educational institutions, help them to comprehend what is meant by e-learning, and what the potential benefits can achieve (Al Musawi & Abdelraheem, 2004).

3.2 Definition of E-Learning

There are many definitions regarding e-learning such as Online Learning-OL, Web-Based Training-WBT, Mobile or m-Learning, Web-Based Instruction-WBI, Web-Based Learning: WBL, Distributed Learning-DL, Internet-Based Training-IBT, Advanced Distributed Learning- ADL, Nomadic Learning, Off-site Learning, Remote Learning, and a-learning: anyplace, anytime, anywhere learning (Khan, 2005).

Additionally, e-learning comprises of the following terms: distance education, distance learning, distance teaching, online education, online learning, distributed learning and web-enabled education. In the same vein, terms like "electronic learning" are used at present (Dealtry, Macpherson, Homan, & Wilkinson, 2005).

Urdan and Weggen (2000) defined the e-learning as the delivery of content through all electronic media, including the internet, audio/video tape, satellite broadcast, CD-ROM and interactive TV. According to Khan (2005), e-learning was defined as:

“An innovative approach for delivering well-designed, learner-cantered, interactive, and facilitated learning environment to anyone, anyplace, anytime by utilizing the attributes and resources of various digital technologies along with other forms of learning materials suited for open, flexible, and distributed learning environment”(p. 3).

In the same context, Hunjak and Begičević (2006) argued that e-learning is:

“A type of learning supported by information and communication technology (ICT) that improves the quality of teaching and learning.” (p.3).

Similarly, Hadjiathanasiou (2009) mentioned that e-learning can occur in the halls of the universities, from home and at the workplace, not limited to one area. Qazaq (2012) pointed out that e-learning can be used for teaching via any electronic techniques involved but not limited to the Internet, DVD, videotape, and CD-Rom. Consequently, e-learning supports students to learn wherever and whenever they want as well as provides flexible access to the teaching materials at the learner's convenience.

3.3 Importance of E-Learning

The design of e-learning is different from traditional classroom in the education process, the traditional learning is a closed system, and space-bound but e-learning is more flexible in this process (Khan, 2005). Qazaq (2012) stated nine advantages of applying e-learning in education as follows: (1) allowing collaborative learning, (2) engaging users, (3) the accommodation of multiple learning styles, (4) providing self-paced instruction, (5) offering individualized instruction, (6) offering on-demand access, (7) increasing consistency, (8) increasing retention, and (9) tracking learners. Also, e-learning can aid academic staff to support and enhance learning (Contino, 2005). Qazaq (2012) argued that:

“Literature is rich with evidence that implementing e-learning at universities can be more time efficient. All members then potentially get more available work – time for research. Time considered very important to spend writing more articles and attending conferences.” (p. 33)

In order to know and deeply understand the difference between e-learning and classroom learning, a comparison between these systems is shown in Table 3.1.

Table 3.1

The Difference between Classroom Learning and E-learning

Classroom Learning	E-learning
Textbooks and reading lists	Content portals and online resources
Chalk and talk	Rich multimedia & interactive content
Class discussion	Inter-classroom collaboration online
Help after class	Web-based tutoring on demand
Quarterly report cards	Real-time student information system (SIS)
On school grounds	Multiple locations

Source: Khan (2007, p34)

Table 3.1 shown that the educator in traditional classroom teaching method always serves the students face to face like: explanation in class, discussion, help after class and so forth. While, in e-learning setting, the educator does not need to teach the students face to face. E-learning can offer as a stimulant for modification in teaching and learning by online courses.

3.4 E-Learning in Malaysia

Malaysia has started the development of e-learning since the second phase of vision 2020 under the Ninth Malaysia Plan (2006 – 2010). According to Goi and Ng (2009), Tun Abdullah bin Haji Ahmad Badawi, former Prime Minister of Malaysia, mentioned that:

“The Government is interested in continuously developing the people by promoting a ‘Continuous Learning Concept’ at the industry,

organization and individual level in both the public and private sectors. The Government will set up the national ‘Lifelong Learning Council’ and all public, and private higher educational institutions should establish one center of life-long learning” (p.1)

Malaysian experiment intended to present an extensive information technology and e-learning to the education field (Al-rahmi, Othman, & Mi Yusuf, 2015). The Education Act 1996 has been issued to present computer systems to link all schools through the Internet, which was anticipated to be finished in 2000, but the financial jolt in 1997 prevented the completion of this plan. Nonetheless, the internet was linked to schools in 1999 by 90%. Malaysian internet project was applied to most local schools and smart technical schools; the project aims to connect schools and universities through column backbone of the fiber optic network, which allows the transfer and exchange of multimedia information on the internet (Goi & Ng, 2009). Malaysia is a fast-developing country in the education sector as well as the adoption of informatics. It is moving aggressively towards building an efficient and successful economy (Azhari & Ming, 2015). According to Watkins (2005):

“We need greater speed, more efficiency, and effectiveness in all endeavours. For this, we need all the knowledge and information that we can get from all sources, and from around the world” (p. 59).

3.5 E-Learning Approaches

The most common concept of integrating digital technology in learning are namely: distance (remote) learning includes synchronous and asynchronous learning, blended learning, flipped classroom and ICT supported face-to-face learning (Begičević, Divjak, & Hunjak, 2007; Kim, Heo, & Lee, 2015; Manca & Ranieri, 2016). The

following five subsections discuss in detail about each e-learning approach which become the focus of the case study in this research.

3.5.1 Asynchronous Learning Approach

This type of remote e-learning does not require students and teachers to be online at the same time. Goodwin, Graham, and Scarborough (2001) defined asynchronous learning as a learning environment that enables learners to communicate with the remote learning sources, instructors, and other learners. However, they are not needed to be on the internet (online) at the same time. This approach consists of a one-way communication between instructors and students. In the same vein, instructors send materials to learners and obtain their individual tasks (assignments). There is no two-way interaction (like discussion, video conferencing where learners get the materials, send feedback, and/or submit the task at the same time) between instructors learners and, or among the learners themselves (Wagner, Hassanein, & Head, 2008). In other words, the learner can look at the website to access the learning materials at any time (Kaur, 2013).

Despite the flexibility of selecting the place and time by learners themselves, there is little get in touch with between the instructors themselves, learners with instructors and learners with the members of the organization (Behling, Orczyk, & Jenkins, 2007). The advantage of asynchronous e-learning is that the student will be able to choose the suitable time for him to access what he needs, and will allow him to do his learning at his own pace.

On the other hand, with this type of e-learning students will be unable to get immediate feedback from the instructor and will be more isolated than synchronous e-learning. But as yet in both types of e-learning, the students need to be motivated for learning in order to overcome the negative effects of the separation between from one another and from their instructor (Brame, 2013). A number of tools could be used to conduct asynchronous e-learning such as e-mail and discussion boards. The following examples clarify how the Asynchronous Learning provides the courses and topics to the remote students (Behling et al., 2007):

- Videotapes are used to deliver course materials.
- Course materials are delivered by CD ROM or website.
- Course materials are delivered via audiotape/ audio cassettes.

The learners can select the place and time to access the courses as offered in the previous examples.

3.5.2 Synchronous Learning Approach

The technological advancement, particularly in the information and communication area, has made the transfer, storage space, and the sharing of information between instructors and students much easier. This procedure is called synchronous distance learning.

Within this setting of distance learning, the learning takes place in actual time. Learners should be registered in course (class) and attend this course in a specific time (scheduling). The get in touch with between the learners and instructors take place electronically throughout the course time (Wagner et al., 2008). For this

reason, this type of e-learning needs modern equipment and good network connection. However, it has the advantage of immediate feedback and lives online interaction. To conduct the synchronous e-learning, there are a number of tools that could be used to be useful for supporting collaborative learning efforts such as video conferencing, audio conferencing, chat rooms, Skype and white board (Mylott, 2008). The following examples clarify how synchronous learning provides the topics and courses to the remote students (Behling et al., 2007):

- Courses are taken via audio conferencing.
- Using online lectures to conduct the distance learning lectures.
- Deliver the distance learning materials to the remote students via television broadcast.
- Courses are offered via video conferencing lectures.
- Use the radio technology to convey the materials to the remote students.

3.5.3 Blended Learning Approach

Blended learning has been presented as a manner of teaching which is enabling interactions between students and teachers effectively, using a variety of instructional methods with ICT. Rovai and Jordan (2004) defined blended learning as:

“A mix of classroom and online learning that includes some of the conveniences of online courses without the complete loss of face-to-face contact” (p. 1).

Similarly, Verkroost, Meijerink, Lintsen, and Veen (2008) defined the blended learning approach as the total mix of pedagogical approaches, using a variety of

learning strategies with technology. When technology is used for learning in the traditional classroom, a blended learning environment is created. Blended learning is created when at least two different techniques of learning and teaching are integrated.

The blended learning approach is expected to enhance student participation. Generally, students come to be more active due to of the new needs to participate and obtain more engaged in the class based on objectives and course design. Masie (2002) argued that the mix of online and classroom learning modes offers the students with the most effective learning experience from both face to face and online. Undoubtedly, a blended learning approach can give assistance for included interaction and opportunities for peer leaning. Masie (2002) noted in support of Blended Learning:

“People are not single-method learners,” and “the magic is in the mix”
(p. 58).

Barlow (2008) found that students utilized the classroom blog site not only at school but also at home, at their friends’ houses, on their mobile phones or on other mobile devices. When students engage in learning outside of the traditional classroom, the students stay engaged, enhancing learning. More commonly, the blended learning is the combination of face-to-face teaching (traditional learning) and ICT (e.g. online learning, e-learning or computer-mediated) as shown in Figure 3.1.

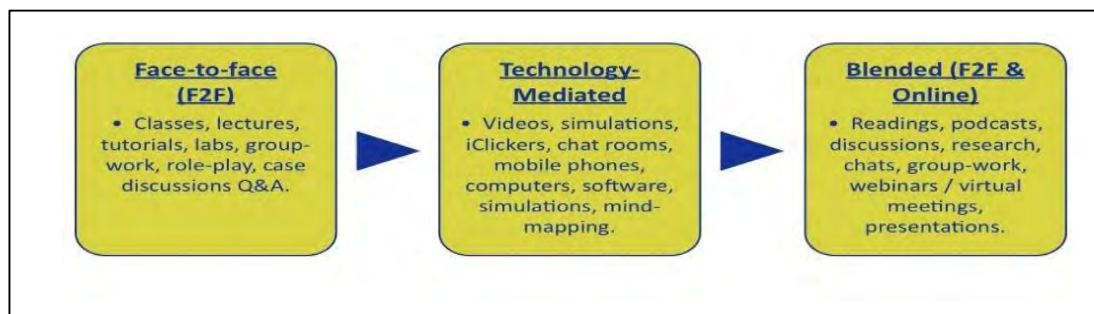


Figure 3.1. Blended learning approach

Figure 3.1 illustrated the mix relation in between traditional class and using technology in class. Furthermore, Moskal, Dziuban, and Hartman (2013) took advantage of this concept by suggesting that it is a pedagogical style and should be seen as a fundamental shift in the instructional approaches.

3.5.4 ICT Supported Face to Face (traditional) Learning

The simple definition of traditional learning is face-to-face learning. This way is used by the teaching staff in the lecture rooms. The students meet with the instructor at the same time in one place and mainly relying on the teacher for lecturing and discussing the topics with them. Schiller (2009) has mentioned that the traditional face-to-face classes were generally thought to be those where the professor is the primary source of knowledge and lectures are the primary delivery method. ICT used as supporting in education process with traditional classes to illustrate some of the ideas by the teacher with use ICT (Video, YouTube, pictures or PowerPoint) through data show in the classroom.

3.5.5 Flipped Classroom Approach

Flipped classroom approach has taken place in education as a new teaching method. It includes any use of using internet technology to influence the learning in the classroom, and thus the teacher will spend more time interacting with students instead of lecturing (Galindo, 2014). The flipped classroom became one modern technical solution for treatment of traditional learning and development level of ability thinking for the student. This is analogous with Bloom's revised Taxonomy in which higher levels of cognitive work are performed outside of the classroom. According to the revised Bloom' taxonomy, students investigate in the flipped classroom the minimum level of the domain knowledge (getting knowledge and assimilations) at home, and concentrate on the top of the domain knowledge (applications, analysis, evaluation) in the classroom time, as shown in Figure 3.2 (Brame, 2013).

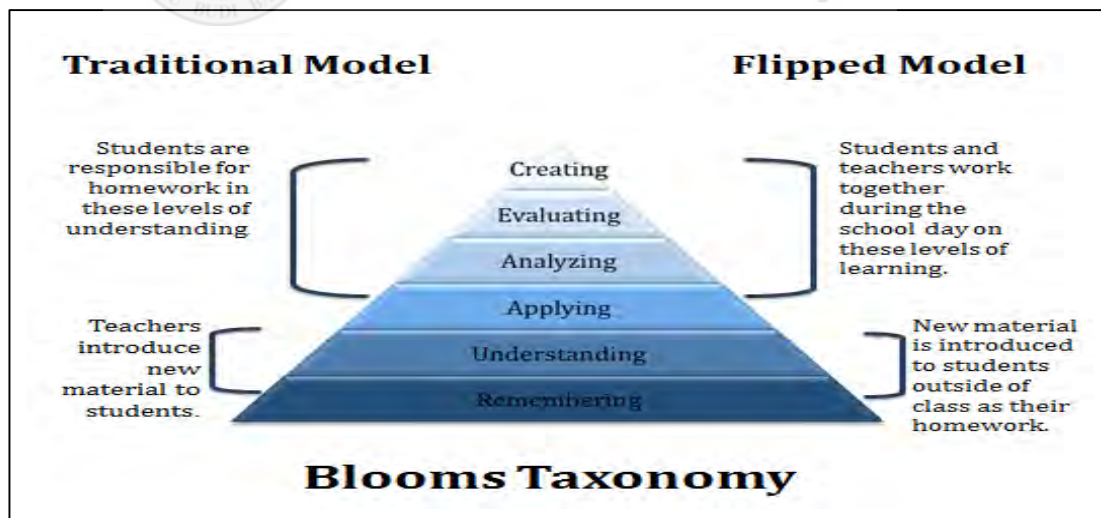


Figure 3.2. Flipped classroom approach

According to Hamdan, McKnight, McKnight, and Arfstrom (2013) the flipped classroom approach, there is a deliberate shift from a teacher-centred classroom to a student-centered approach. Flipped classroom approach has started to become common on many university campuses.

The idea is based on flipped classroom, where students receive the new concepts inside the classroom and then go back to their homes to do their homework in traditional learning. In this approach, the students will receive the new concepts at home through the teacher preparation videos by using assistance programs between 5-10 minutes and participation in social network such as: KHAN Academy for education, YouTube, iTunes University, or others learning websites (Bergmann & Sams, 2012). The students also can learn new concepts at home through using modern technology such as smart phones, laptops, or iPads (Galindo, 2014). Students can review the video several times to understand the new concepts; they can also speed up the section to escape the section which they already understand. The mind is up to the individual difference between the students and the boredom element will disappear and will be replaced by a thrill and joy of learning.

Teachers can also set up an electronic test (Quiz) for the concepts of new lessons; students answer questions which help the teacher identify the strengths and weaknesses in the assimilated level of understanding (Herreid et al., 2012). The flipped classroom approach introduce mixing between two unique theories of learning which were viewed as non-compatible, traditional learning and active learning (Bishop & Verleger, 2013).

3.6 Decision Making of E-Learning

Decision-making process and strategic planning about application of e-learning approaches have been covered as involving of four phases: the first is intelligence, the second is design, the third phase is a choice and the last phase is about the implementation (Begičević & Divjak, 2006).

- I. **Intelligence phase.** The Intelligence phase is identifying the problems. To figure out how many criteria or attributes exist in the problem and how to understand the way of the problems, through conduct search and scanning procedures, perform a situation analysis, determine problem ownership, and finally present a problem statement. In this study, the central decision-making problem has been determined, and that is decision-making about application of e-learning approaches in higher education.
- II. **Design phase.** In this stage, the design phase relies on the outcomes of the Intelligence phase for the establishment alternatives, criteria and develop a theoretical model about application of e-learning approaches for decision-making. In this stage, the appropriate gathering information is needed to extract the alternatives and most important criteria for the decision-making process. In this study, there are five alternatives being studied: (1) ICT supported face-to-face learning, (2) blended learning, (3) flipped classroom learning, (4) synchronous learning, and (5) asynchronous learning. In the past, there were some researchers had presented many criteria and sub-criteria about the e-learning. In this study has been chosen suitable criteria about e-learning approaches from the literature based on available alternatives in this research. The most important criteria serve as input in the MCDM techniques.

- III. **Choice phase.** In this stage, the MCDM techniques were used to evaluate the alternatives with regard to e-learning approach that support decision-making process to select the most suitable alternative.
- IV. **Implementation phase.** The last stage is the application of e-learning approaches and must be included in the action plan and control system.

3.7 Literature Review about E-Learning Using MCDM Methods

Colace et al. (2006) proposed a model evaluating and selection of e-learning platform (synchronous and asynchronous) through five of multiple criteria, using AHP method to measure the performances of a commercial platform with four types of e-learning platform (IWT, ACHAB, DOCENT and RUNNING PLATFORM). They had also made comparisons among three scenarios (ECDL course, blended course, and professional training). They suggested this method's effectiveness in the considered scenario. Thus, their results showed that the DOCENT is the most important in three scenarios of other types of e-learning platforms.

Hunjak and Begičević (2006) determined the priorities for implementation of e-learning in higher education using AHP method with seven criteria, fifteen sub-criteria and four alternatives of e-learning. The results showed the classes and class contents criterion is the most important than other criteria, and blended learning is the most suitable alternative for applying e-learning in organizations. Moreover, they indicated to a real need for systematic e-learning model usage in educational institutions.

Beginčević et al. (2007) made prioritization for criteria and alternatives about e-learning system using AHP method with five criteria, twenty-two sub-criteria and three alternatives. They found that the blended learning is the most important in e-learning programming in higher education.

Tzeng et al. (2007) conducted a pilot study about training coerces between some companies by using e-learning program to reduce the time and cost. The researchers proposed new novel hybrid MCDM model for an effective assessment of the relations between the criteria using AHP method and fuzzy integral method with 58 criterion of e-learning criteria. The results showed that the proposed model could make effective evaluations with suitable criteria for perceptions of DMs.

Shee and Wang (2008) evaluated the Web-based e-learning system (WELS) criteria relying on e-learner-satisfaction perspective using AHP method with four criteria and thirteen sub-criteria. They found that the learner interface criterion is the most important criteria of decision criteria for distance learning.

Chao and Chen (2009) illustrated an empirical example by evaluating some criteria about distance web e-learning including synchronous and asynchronous learning. They utilized the consistent fuzzy preference valuation in AHP method with five main criteria and sixteen sub-criteria. The results showed that the e-learning material criterion is the most important criteria, and these evaluations can provide important information to the DMs of school for distance learning.

Büyüközkan, Arsenyan, and Ertek (2010) evaluated the quality of criteria for e-learning Websites using fuzzy TOPSIS and fuzzy AHP methods in order to validate

the results. Seven main criteria were limited as the e-learning Website quality dimensions, and twelve of alternatives for e-learning Website were available. Their results showed that the website number 11 was the most important alternative to the alternatives.

Sadi-Nezhad et al. (2010) presented FANP method for evaluating e-learning based on twelve criteria and made comparisons among three types of e-learning platforms for distance learning. Their study was compared between AHP and ANP methods with three proposed scenarios.

Stefanovic, Tadic, Arsovski, Arsovski, and Aleksic (2010) introduced FMCDM method for e-learning quality assessment with ten criteria regarding e-training process, and they decomposed the e-learning system into subprocesses and activities. They determined priorities criteria for e-learning. Moreover, they found that this method enables comparison of various e-training procedures and their ranking based on the level of quality.

Mehregan et al. (2011) introduced a new approach for e-learning system evaluating by identity and prioritizing the e-learning critical success factors using FAHP method with six main criteria and twenty-two sub-criteria for distance e-learning. Moreover, they found that the student characteristics criterion was the most important in an e-learning system.

Tai et al. (2011) presented the fuzzy linguistic evaluation for e-learning using AHP and TOPSIS methods with thirty criteria depending on Web Resources. They

recommended that this assessment could be used as references by users and e-learning research.

Syamsuddin (2012) developed frameworks for e-learning software evaluation using FAHP method with six main criteria and twenty-two sub-criteria based on the ISO9126 model. They recommended that the framework support group decision making is to evaluate a large number of e-learning software.

Kupenko, Lavryk, Barchenko, and Lavrov (2013) investigated prioritization criteria weight using AHP method with twelve criteria about e-learning. After that, they excluded the least important criteria, then only five criteria were used in the model of Ergonomic Expertise on fuzzy logic for the development of a repository educational resources through distance e-learning. Their results have shown that the consistency and standards with flexibility and efficiency criteria were important in e-learning.

Su et al. (2013) conducted empirical tests to address the dependent relationships among the different criteria companion for cloud e-learning service by using DEMATEL based on ANP method (DANP) with three dimensions and twelve criteria about distance learning. Overall, their results may be valuable for practitioners and researchers both to expand the e-learning development.

Wu and Chen (2013) conducted an empirical study of the e-learning platform (synchronous and asynchronous Web-based) in improving learning efficiency among the students in management and technology based courses. Overall, the results have shown that information use dimension was the most important in technology courses.

Munkhtsetseg et al. (2014) described the selection and application of the e-learning using MCDM method with four criteria and thirteen sub-criteria for distance learning about training classes in organizations. They found that e-training needed to have a close collaboration between information technology and the educational experts.

The related studies mentioned above are summarized in Table 3.2.

Table 3.2

Related Studies

Authors	E-learning approaches	MCDM technique
Colace et al. (2006)	Distance learning	AHP
Hunjak and Begičević (2006)	Blended learning, online learning	AHP
Begičević et al. (2007)	Blended supported learning, face to face learning, online learning	AHP
Tzeng et al. (2007)	Online learning	FAHP
Shee and Wang (2008)	Web-based e-learning system (WELS)	AHP
Chao and Chen (2009)	distance web e-learning	FAHP
Büyüközkan et al. (2010)	E-learning Websites	Fuzzy TOPSIS and FAHP
Sadi-Nezhad et al. (2010)	Distance learning	FANP and FAHP
Stefanovic et al. (2010)	Distance learning	FMCDM

Table 3.2. *Continued*

Stefanovic et al. (2010)	Distance learning	FMCDM
Mehregan et al. (2011)	Distance learning	FAHP
Tai et al. (2011)	Distance learning	AHP and TOPSIS
Syamsuddin (2012)	Distance learning	FAHP
Kupenko et al. (2013)	Distance learning	AHP
Su et al. (2013)	Distance learning	DEMATEL ANP
Wu and Chen (2013)	Synchronous and Asynchronous Web-based	AHP
Munkhtsetseg et al. (2014)	Distance learning	AHP

Table 3.2 displayed evaluation of different e-learning approaches introduced by different authors in literature using MCDM techniques. Most of these researches show that distance learning or online learning are assessed by AHP technique. In this study, different e-learning approaches were evaluated by different MCDM methods. Specifically, the criteria weights of the e-learning approaches were assessed and analysed by several subjective weighting methods.

3.8 Criteria of E-Learning

Due to the fact that there is still growth in e-learning, it's hard to ascertain the criteria for e-learning concept. Nonetheless, criteria should be based on the degree of

stability and consistency. Thus, there are different criteria proposed by several researchers about e-learning as shown in Table 3.3.

Table 3.3

E-learning Criteria from Previous Studies

Criteria	Authors
Contents	Hunjak and Begicevic (2006), Shee and Wang (2008), Sadi-Nezhad et al. (2010), Munkhtsetseg et al. (2014), Buyukozkan et al. (2010), Stefanovic et al. (2010), Mehregan et al. (2011), Lavrov et al. (2013), and Su et al. (2013).
Individual Learning	Wu and Chen (2013), Buyukozkan et al. (2010), Chao and Chen (2009), Shee and Wang (2008), Sadi-Nezhad et al. (2010), and Munkhtsetseg et al. (2014).
Cooperation and Interactivity	Stefanovic et al. (2010), Mehregan et al. (2011), Wu and Chen (2013), Buyukozkan et al. (2010), Colace et al. (2006), and Colace et al. (2006).
Learner Interface	Shee and Wang (2008), Sadi-Nezhad et al. (2010), Munkhtsetseg et al. (2014), and Buyukozkan et al. (2010).
Usability	Colace et al. (2006), Lavrov et al. (2013), Syamsuddin (2012), and Stefanovic et al. (2010).
Flexibility and Adaptability	Stefanovic et al. (2010), Lavrov et al. (2013), and Colace et al. (2006).
Quality of Service	Su et al. (2013), Mehregan et al. (2011), and Chao and Chen (2009).
Learning Community	Shee and Wang (2008), Sadi-Nezhad et al. (2010), and Munkhtsetseg et al. (2014).
Management	Colace et al. (2006), Lavrov et al. (2013), and Su et al. (2013).

Based on the literature, there are different criteria proposed by several authors about e-learning as displayed in Table 3.3 as groups of authors on the same criteria. Based on the Table 3.3, the contents criterion had been chosen from different nine studies in e-learning. Also, different six studies about e-learning were selected the individual learning criterion as the one of important criteria in e-learning. However, only three studies were considered the management as the one of criteria in e-learning.

3.9 Summary and Discussion

This chapter illustrates the different types of e-learning. It also touches on the decision-making process more about e-learning and also criteria for e-learning approaches as well as some related studies.

From the literature review about e-learning using MCDM methods, some researchers concentrated on distance learning or online learning on training process in organizations via training courses online. Other researchers concentrated on distance learning in higher education which includes synchronous and asynchronous learning. Thus, the students can get their certificates without attending class. However, one of criticism about distance learning is that the students have difficulty in expressing their views and their ideas in writing, where a lot of students prefer to express their views orally. This may lead to a lack of motivation toward learning as well as boredom as a result of sitting in front of a computer for a long time. Accordingly, it does not give the educational value, the student will lose their active participation in class, such as lectures, discussions, questions, group work, assignments and professor's view and perspectives (Arkorful & Abaidoo, 2015).

Some researchers concentrated on comparing distance learning which includes synchronous and asynchronous learning with teaching methods in the classroom (traditional learning and blended learning) by using MCDM methods. The finding of their research showed that the blended learning is the best approach of teaching methods. There are no studies being conducted on the comparison of MCDM with integrated flipped classroom approach, the newest teaching procedure in e-learning. The methodology of this current study is discussed further in the next chapter.

CHAPTER FOUR

RESEARCH METHODOLOGY

4.1 Introduction

Due to unavailability of a framework to decide the optimal subjective weighting method, this research aims to develop decision framework on selecting the optimal subjective weighting method for solving MCDM problems. Specifically, the research aims to select the optimal subjective weighting method or the most accurate weights from DMs' perspectives, so to produce a somewhat more reliable set of criteria weights. Furthermore, the Pairwise Comparisons (PCs) technique is one of subjective weighting methods, and it has inconsistency problems, especially with a large number of criteria. As mentioned previously, the large number of criteria may lead to inconsistent judgments, and these judgments may need to be revised by DM several times. Therefore, this study proposed the Tripartite Relations for Overcoming Inconsistency (TROI) method to address this issue in order to be integrated into this decision framework through comparison among several subjective weighting methods.

The e-learning approaches contain several elements to improve student's learning and educational development process in higher education through applying modern teaching methods to become useful educational approaches for higher education. This study focuses on evaluating e-learning approaches namely: Blended learning, flipped classroom, ICT supported face-to-face learning, synchronous, and asynchronous learning as modern teaching methods by using MCDM techniques. These techniques include criteria of differing importance to DMs. Then, details

regarding the relative importance of the criteria are needed, and this typically realized by assigning a weight to each criterion. The proposed decision framework would be applied on evaluating e-learning approaches. The purpose of this chapter is to describe the methodology in achieving the research objectives.

4.2 Research Framework

The decision framework of this research is developed to select optimal subjective weighting method by the comparison among several subjective weighting methods as discussed in the following steps. To demonstrate weighting process and to obtain different sets of attributes weights from utilizing of nine weighting methods, the geometric average of all nine weights is defined as ideal weights, to be compared with each weighting method in order to achieve the most accurate weights. This framework aims to decide the optimal weighting method to be used in evaluating different e-learning approaches.

The data were collected from the selected public university in 2016 through two sets of a questionnaire which had been established by using Google Drive and then sent to participants through emails. The first set is about the importance of criteria towards implementation of e-learning, while the second set of the questionnaire concerns about the rating of the performance of each of the e-learning approach under every criterion (see Appendix A).

The primary objective of this study is to develop a decision framework for selecting the optimal subjective weighting method for evaluating e-learning approaches. The key steps of the study to achieve the main objective are described in the following

steps and followed by Figure 4.1 that summarizes the structure of the decision framework.

Step 1: Determining e-learning criteria and alternatives on the modern teaching methods through literature review. In this study, five criteria of e-learning, as well as five types of alternatives regarding e-learning were gathered from literature surveys.

Step 2: The survey was conducted in a selected public university in Malaysia by sending the questionnaire to more than 700 people through emails obtained from the university website. The ranking or scoring on evaluating e-learning criteria and e-learning approaches were collected from the respondents and divided into three different groups, administrative (see Appendix B), academic staff (see Appendix C), and postgraduate students (see Appendix D).

Step 3: Based on the evaluation of each criterion given by each respondent, criteria weights have been analyzed by using nine different subjective weights methods namely: Rating Method (RM), Rank Order Centroid (ROC), Rank Exponent (RE), Rank Reciprocal (RR), Rank Sum (RS), Ratio Weights (RW), Graphical Weights (GW), Direct Point Allocation (DPA), and Pairwise Comparisons (PCs) (see Appendix F). Matrix Laboratory (MATLAB) language program was used for calculating all the processes mentioned above (see Appendix G).

Step 4: The PCs needs to consistency check. Normally, if the consistency ratio is less than 10%, then the criteria weights are acceptable or consistent. However, if the consistency ratio is more than 10%, then the criteria weights are unacceptable or inconsistent. The inconsistency evaluations need to be revised by the DMs to get new

scores or ranks about criteria. The researchers will face problems with inconsistency cases, where the researchers need to revise the judgments with the DMs may be several times. In this study, a proposed method was presented for overcoming the inconsistency problem in PCs method. It is called Tripartite Relations for Overcoming Inconsistency (TROI). The details in addressing the inconsistent criteria weights by using proposed TROI method is discussed in Chapter Four. MATLAB language program was used for TROI method (see Appendix H).

Step 5: The Geometric average (G. Mean) of each groups' weights of each method was calculated. After that, the G. Mean weights were normalized by dividing each G. Mean weight with the sum of G. Mean weights to guarantee that the sum of these final weights is equal to one. Next, the G. Mean has used once again for each criterion from each method of all groups. Then the weights were normalized once again to make sure that the sum of weights is one. These normalized weights are declared as the Ideal Weights (IW). This way is essential for avoiding inaccurate weights of the MCDM methods and obtaining positive outcomes.

Step 6: In order to determine the most accurate weights method, the absolute difference between IW and each weights method (ROC, RE, RR, RS, RM, RW, DPA, GW, and PCs) for the same respective criterion was calculated. After that, the sum of all absolute differences for each weights method was calculated, and the method that has the smallest sum of absolute difference would be declared as the most accurate method.

Step 7: Based on the identified e-learning approaches which include blended learning, flipped classroom, ICT supported face-to-face learning, synchronous and

asynchronous learning, another set of the questionnaire was developed that focuses on the assessment of the selected e-learning approaches under the identified evaluation criteria. The respondents had to rate how essential each of the criteria towards implementation of each of the e-learning approaches.

Step 8: Checking the accuracy of the ranking of the e-learning approaches. The set of optimal weights method was then used to select the most suitable e-learning approach by using TOPSIS method.

Step 9: Ranking of alternatives and choose the best method of modern teaching methods of e-learning. Finally, validate or confirm final result with DMs by questionnaire (see Appendix I).



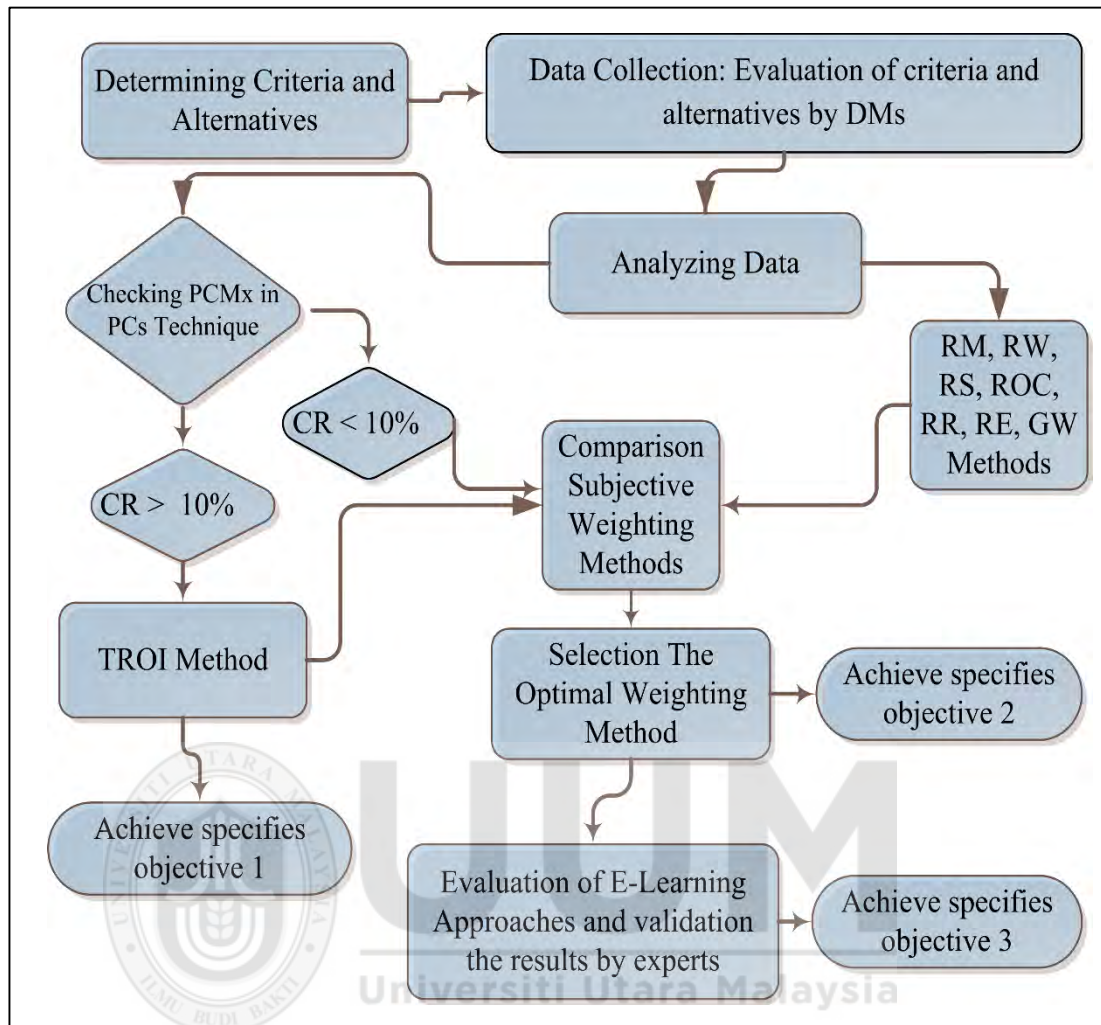


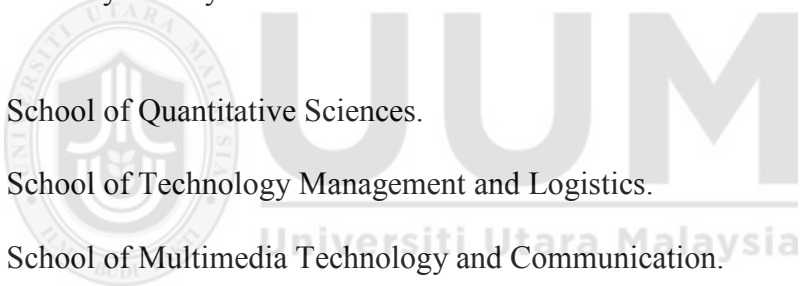
Figure 4.1. The development of the proposed decision framework

4.3 Data Collection Procedures

The data were collected from the selected public university in 2016 through an online questionnaire which had been established by using Google Drive and then sent to participants through emails. In order to assign weights to the selected criteria and alternatives, two types of questionnaire were used to obtain the respondents' perceptions. The first set of questionnaire was for analysing criteria weights by using nine subjective weights methods as mentioned previously with five questions regarding each method. It is about the importance of criteria towards implementation

of e-learning as shown in Appendix A (questions 1-5). In this questionnaire, the respondents were required to rank the criteria in an order based on their perception and experience. The second set of questionnaire was for choosing the most suitable approach of e-learning by using TOPSIS technique as shown in Appendix A (question 6). It concerns about the rating of the performance of each of the e-learning approaches under every criterion.

The questionnaire has been distributed from the 7th of March to the 4th of April in 2016, into all schools in the selected university (ten schools) after identifying e-learning criteria and alternatives. The data were collected from ten different schools in the university namely:

- 
- I. School of Quantitative Sciences.
 - II. School of Technology Management and Logistics.
 - III. School of Multimedia Technology and Communication.
 - IV. School of Islamic Finance and Banking.
 - V. School of Education and Modern Languages.
 - VI. School of Economics Finance and Banking.
 - VII. School of Computing.
 - VIII. School of Business Management.
 - IX. School of Accountancy.
 - X. School of Law.

The questionnaire was sent through email to more than 700 people from different departments. A total of 109 participants took part in the survey, and after checking, a total of 95 participants gave their responses correctly (based on the questions). The

data collected was divided into three groups namely: administrative, academic staff, and postgraduate students.

4.4 The Profile of the Respondents

In this study, ten schools and their departments were involved. The collection of data took approximately one month. The respondents in this study consisted of three groups, administrators, academic staff, and postgraduate students. A total of 22 responses from the administrative group have been received which included the dean, deputy dean, head of the department, and coordinator. There were 38 responses received from the academic group which included professors, associate professors, senior lecturer, and lecturer. A total of 35 participants were postgraduate students who were pursuing Masters and Ph.D. Table 4.1 displays the detailed numbers regarding the academic qualification of the respondents in each group.

Table 4.1

The Academic Qualification of Groups

No.	Name of Group	Number of Participants	Academic Qualification		
			Ph.D.	M.A.	BA
1	Administrative	22	22		
2	Academic staff	38	25	13	
3	Postgraduate students	35		24	11

The detailed numbers regarding the academic title and position of the respondents in each group are provided in Table 4.2.

Table 4.2

The Academic Title and Position of Respondents

No.	Name of Group	Title (number)	Position (number)
1	Administrative	Assoc. Prof. (15) Senior Lecturer (7)	Coordinators (9) Head of Departments (7) Deputy Dean (4) Dean (2).
2	Academic staff	Prof. (1) Assoc. Prof. (3) Senior Lecturer (20), Lecturer (14)	Teachers (38)
3	Postgraduate students	Ph.D. students (24) Masters Students (11).	Students (35)

The respondents were asked to evaluate the importance of criteria towards implementation of e-learning, as well as rating the performance of each of the e-learning approaches under every criterion.

4.5 Questionnaire Description

In order to assign weights to the selected criteria, the questionnaire approach was used to the order of criteria and performance scores. Two types of questionnaire were used to obtain the respondents' perceptions. The first set of questionnaire was for calculating criteria weights (see Appendix A, Questions 1-5), and the second set of questionnaire was for choosing the most suitable model of e-learning (see Appendix A, Question 6) as shown in questions statement below.

Question 1- Identify the most important of e-learning criterion and give it a rating of 100. Next, rate each of the other criteria in turn on a scale of 10–90, to indicate how

important they would be compared to the most important criterion. This issue required for using RM method.

Question 2- Identify importance e-learning criteria and give it a rank of 1 to 5. This issue needed to using Ranking methods (RR, RS, RE, and ROC).

Question 3- Identify the least important criterion and give it a rating of 10. Next, consider each of the other criteria in turn and indicate how important they would be compared to the least important criterion. This issue required for using RW method.

Question 4- Identify the important criterion and give it a rating of 5 to 100. The total of all factors (criteria) weights must be summed up to 100. This question required for using DPA method.

Question 5- Using the scale of 1 to 9 with a choice from equally important 1 to extremely important 9, please rate the following factors (criteria) with respect to their reciprocal criterion. This issue needed to use GW and PCs methods.

Question 6- Evaluate the importance of each criterion for each e-learning approach and give it a rating or score about the importance of each approach with respect to each criterion from 10 to 100. This question was for choosing the most suitable approach of e-learning by using TOPSIS technique.

4.6 Geometric Mean

There are various methods to calculate the average of values. Arithmetic Mean (A. Mean), Harmonic Mean (H. Mean), and Geometric Mean (G. Mean) are popular

methods in mathematical to computing the average. A. Mean is the sum of the values divided by the number of values. The A. Mean ($\bar{x}$) is given in Equation (4.1).

$$\begin{aligned}\bar{x} &= \frac{x_1 + x_2 + \dots + x_n}{n} \\ &= \frac{1}{n} \sum_{i=1}^n x_i\end{aligned}\tag{4.1}$$

H. Mean is the inverse of the arithmetic average of the inverse of the given values. As shown in Equation (4.2).

$$H. Mean = \frac{n}{\sum_{i=1}^n \left(\frac{1}{x_i}\right)}\tag{4.2}$$

The G. Mean of a set of containing n of values is the n th root of the result of the values. The G. Mean is given in Equation (4.3).

$$\begin{aligned}\bar{a}_{ij} &= \frac{a_{ij}}{\sum_{i=1}^n a_{ij}} \\ G. Mean &= \left(\prod_{i=1}^n \bar{a}_{ij} \right)^{\frac{1}{n}}\end{aligned}\tag{4.3}$$

For all positive data sets, the H. Mean is always the least of the three means, while the A. Mean is always the greatest of the three, and the G. Mean is always in between (Smith, 1988). Therefore, the G. Mean has been used in all calculating processes with regard to the average in this study.

4.7 Data Analysis Techniques

The purpose of this research is to propose a decision framework on selecting the optimal weighting method among several methods of subjective weighting methods. Since the decision framework is implemented in deciding the criteria weights of e-learning, this section focuses on how the decision framework is used to decide the optimal weights of e-learning criteria. A priority ranking of criteria was established from the survey participants' preferences through a questionnaire. The scoring or ranking on five criteria has been obtained from 95 participants about e-learning approaches in the selected university. The weights of the criteria were analyzed by using nine different subjective weighting methods (ROC, RE, RR, RS, RM, RW, DPA, GW, and PCs) as given previously (see Appendix F). The normalized weights from each method have been done, and after that, the G. Mean was used to get the geometric weights from each method for each criterion. Then the weights were normalized once again to make sure that the sum of weights is one.

In order to determine the optimal weights method in this study, the absolute difference between each criterion weight for each method with the IW for the same respective criterion was calculated. After that, the sum of all absolute differences for each weighting method was calculated. The method that has the smallest sum of absolute difference would be declared as the most accurate way. Logically, the real meaning of criteria weights was achieved by using various weighting methods. This way is important for avoiding inaccurate weights of the MCDM methods and obtaining positive outcomes. The procedures of each technique adopted in this research are discussed in the following sections. The weights methods computed with the support of the MATLAB language program (see Appendix G).

4.7.1 Rank Sum (RS) Method

The RS weight is formulated such that the individual weight in RS is normalized by the sum of all attributes' weights (Stillwell, 1981), where each attribute is weighted or calculated as in Equation (4.3).

$$w_i(RS) = \frac{K - r_i + 1}{\sum_{j=1}^K K - r_j + 1} \quad (4.3)$$

Where K is the number of attributes under consideration, r_i is the rank position of the criterion or attribute i , $i = 1, \dots, K$. The weight, w_i is the normalised weight for each criterion i .

The ranking methods questionnaire in Appendix A (question 2) was designed after listing all the criteria and explained the list to the participants. The participants were briefed on how to fill the ranking table and then asked to give most important criterion assigned with Rank-1 and the second most important criterion with Rank-2 and so on. The least important criterion should be given Rank-5. The collected data regarding the criteria importance evaluation from the respondents were analyzed by RS, RR, RE, ROC methods, as observed in numerical examples given in each of those methods based on data collected from the first respondent of the administrative group.

For example, the evaluation and the calculation of weights based on the first respondent of the administrative group are shown in Table 4.3.

Table 4.3

Calculation of the Weight Using RS for One Respondent

Criteria Number	First Respondent's Evaluation (r_i)	Calculation ($K - r_i + 1$)	Normalized Weights
C1	1	5	0.3333
C2	5	1	0.0667
C3	4	2	0.1333
C4	3	3	0.2000
C5	2	4	0.2667
Total			1

4.7.2 Rank Reciprocal Weights (RR) Method

The RR weights are normalized reciprocals of criteria's rank, or by dividing each attribute's reciprocal rank by the sum of the reciprocals of all criteria's ranks (Stillwell, 1981) as given in Equation (4.4).

$$w_i(RR) = \frac{1/r_i}{\sum_{j=1}^K (1/r_j)} \quad (4.4)$$

Where r_i is the rank position of the criterion. For example, the evaluation and the calculation of weights based on the first respondent of the administrative group are shown in Table 4.4.

Table 4.4

Calculation of the Weight Using RR for One Respondent

Criteria Number	First Respondent's Evaluation (r_i)	Calculation ($1/r_i$)	Normalized Weights
C1	1	1	0.4380
C2	5	0.2	0.0876
C3	4	0.25	0.1095
C4	3	0.3333	0.1460
C5	2	0.5	0.2190
Total		2.2833	1

4.7.3 Rank Exponent (RE) Method

The RE method is a generalization of the RS, which is calculated as in Equation (4.5).

$$w_i(RE) = \frac{(K - r_i + 1)^p}{\sum_{j=1}^K (K - r_j + 1)^p} \quad (4.5)$$

Where r_i is the rank of the i – th criterion, K is the number of criteria, p is the parameter describing the attributes, $i = 1, 2, \dots, n$. The parameter may be assessed by a DM using the weight of the most important attribute or via interactive scrolling. If the parameter $p = 0$, the results become equal weights, If the parameter $p = 1$, the results are the same in RS method results. As p increases, the distribution of weights becomes steeper. In this study the weights using RE method are calculated, assuming that $p = 2$.

For example, the evaluation and the calculation of weights based on the first respondent of the administrative group are shown in Table 4.5.

Table 4.5

Calculation of the Weight Using RE for One Respondent

Criteria Number	First Respondent's Evaluation (r_i)	Calculation $(K - r_i + 1)^p$ $p = 2$	Normalized Weights
C1	1	25	0.4545
C2	5	1	0.0182
C3	4	4	0.0727
C4	3	9	0.1636
C5	2	16	0.2909
Total		55	1

4.7.4 Rank-Order Centroid Method (ROC)

Barron and Barrett (1996) showed that the expected value of the weight of each attribute could be computed using the Equation (4.6).

$$w_i(ROC) = \frac{1}{K} \sum_{n=i}^K \frac{1}{n} \quad (4.6)$$

Where K is the number of criteria, n is the rank position of criterion i , $i = 1, 2, \dots, K$. This manner of getting the criteria weights is called ROC because these weights reflect the centre of mass (centroid) of a simplex defined by the ranking of the attributes. With more attributes, the error for ranked attributes will be much less (Roszkowska, 2013). For example, the evaluation and the calculation of weights based on the first respondent of the administrative group are shown in Table 4.6.

Table 4.6

Calculation of the Weight Using ROC for One Respondent

Criteria Number	First Respondent's Evaluation	Calculation $\frac{1}{K} \sum_{n=i}^K \frac{1}{n}$	Normalized Weights
C1	1	$\frac{1}{5}(\frac{1}{1} + \frac{1}{2} + \frac{1}{3} + \frac{1}{4} + \frac{1}{5})$	0.4567
C2	5	$\frac{1}{5}(\frac{1}{5})$	0.0400
C3	4	$\frac{1}{5}(\frac{1}{4} + \frac{1}{5})$	0.0900
C4	3	$\frac{1}{5}(\frac{1}{3} + \frac{1}{4} + \frac{1}{5})$	0.1567
C5	2	$\frac{1}{5}(\frac{1}{2} + \frac{1}{3} + \frac{1}{4} + \frac{1}{5})$	0.2567
Total			1

4.7.5 Rating Weights Method (RM)

In the RM procedure, a score of 100 is assigned to the most important criterion. For the second-ranking criterion, a ratio score corresponding to its importance is

assigned. The value for each criterion is divided with the least important criterion. Let r_i be a weight for criterion i , $i = 1, \dots, n$. Let r^* be the weight for the least important criterion. So the weight for criterion i is r_i/r^* , and then the final weight is found by normalizing the weight. This normalization process will ensure that the sum of all criteria weights is one. Analysing the data collected from the respondents (administrative, academic staff, and postgraduate students) were calculated by RM method. In this method, the participants were asked to identify the utmost importance e-learning criterion and give it a rating of 100. Next, rate each of the other criteria in turn on a scale of 10 – 90, to indicate how important they would be compared to the most important criterion.

For example, the evaluation and the calculation of weights based on the first respondent of the administrative group are shown in Table 4.7.

Table 4.7

Calculation of the Weight Using RM for One Respondent

Criteria Number	First Respondent's Evaluation (r_i)	Calculation (r_i/r^*) $r^* = 40$	Normalized Weights
C1	100	2.5	0.2632
C2	40	1	0.1053
C3	70	1.75	0.1842
C4	80	2	0.2105
C5	90	2.25	0.2368
Total		9.5	1

4.7.6 Point Allocation Weights Method (DPA)

In DPA process, the DM has a 'budget' of points to assign the attributes directly to reflect their relative importance. The total of all attribute weights must be sum up to

100. In this study, the participants were asked to identify the important criterion and give it a rating of 5 to 100. The total of all criteria weights must be summed up to 100. This question required for using DPA method.

For example, the evaluation and the calculation of weights based on the first respondent of the administrative group are shown in Table 4.8.

Table 4.8

Calculation of the Weight Using DPA for One Respondent

Criteria Number	First Respondent's Evaluation	Normalized Weights
C1	30	0.3
C2	10	0.1
C3	15	0.15
C4	20	0.2
C5	25	0.25
Total	100	1

4.7.7 Ratio Weighting (RW) Method

The RW method requires the DMs to first rank the related attributes according to their importance. The least important attribute is allocated a weight of ten, and all others are judged as multiples of ten. The weight of a criterion is obtained by dividing the criterion's weight with the sum of all attributes' weights. Participants were asked to identify the least important criterion and give it a rating of 10. Then, they were required to consider each of the other criteria in turn and indicate how important they would be compared to the least important criterion. The data collected from three groups (administrative, academic staff, and postgraduate students) were analyzed by RW method.

For example, the evaluation and the calculation of weights from the first respondent of the administrative group are shown in Table 4.9.

Table 4.9

Calculation of the Weight Using RW for One Respondent

Criteria Number	First Respondent's Evaluation	Normalized Weights
C1	80	0.32
C2	10	0.04
C3	30	0.12
C4	60	0.24
C5	70	0.28
Total		1

4.7.8 Graphical Weights (GW) Method

In the GW technique, selected participants were required to place a mark on a horizontal line (9 – 7 – 5 – 3 – 1 – 3 – 5 – 7 – 9) to give importance to one criterion compared with another criterion. That means, the criterion is either more, equally or less important than another criterion by a factor of 1 – 9, and then build the decision matrix as in pairwise comparison (PCs). The criteria weight can be calculated by taking the sum of each row and then normalized scores to obtain an overall weights vectors.

In GW method, the data were collected from a set of questionnaires by three groups (administrative, academic staff, and postgraduate students). The GW questionnaire (refer to Appendix A) was designed to collect data for PCs and GW methods because the data gathered based on the comparison in between pairs of criteria after explaining the list of criteria to the participants. Furthermore, all the participants

were assumed to have a reasonable knowledge of the e-learning criteria and alternatives.

For example, the evaluation and the calculation of weights from the first respondent of the administrative group are as shown in Figure 4.2 below.

$$PCM_x = \begin{bmatrix} A & B & C & D & E \\ A & 1 & 8 & 6 & 4 & 2 \\ B & 0.12 & 1 & 0.5 & 0.33 & 0.2 \\ C & 0.17 & 2 & 1 & 0.5 & 0.33 \\ D & 0.25 & 3 & 2 & 1 & 0.5 \\ E & 0.5 & 5 & 3 & 2 & 1 \end{bmatrix} \rightarrow \begin{bmatrix} Sum \\ 21 \\ 2.15 \\ 4 \\ 6.75 \\ 11.5 \end{bmatrix} \rightarrow \begin{bmatrix} Normalized Weights \\ 0.4626 \\ 0.0474 \\ 0.0881 \\ 0.1487 \\ 0.2533 \end{bmatrix}$$

Figure 4.2. Illustrative example of GW method

4.7.9 Pairwise Comparisons (PCs) Method

Computing weights using PCs method has five major steps.

Step 1: Develop a matrix comparing the attributes pair wisely by using Saaty's scale (see Table 4.10). The diagonal in the PC matrix is always 1, and the lower left values are inverted values. Let $A = [a_{ij}]_{n \times n}$ be the pairwise comparison matrix with $a_{ji} = 1/a_{ij}$.

Table 4.10

Scale of Relative Importance

Scale of Importance for Pairwise Comparisons	Numeric Rating
Extreme Importance	9
Very strong Importance	7
Strong Importance	5
Moderate Importance	3
Equal Importance	1

Step 2: Calculate the criteria weights by taking the Geometric Mean (G. Mean) of elements in each row as given in Equation (4.7).

$$\bar{a}_{ij} = \frac{a_{ij}}{\sum_i a_{ij}}$$

$$w_i = \left(\prod_{j=1}^n \bar{a}_{ij} \right)^{\frac{1}{n}} \quad (4.7)$$

Step 3: Calculate the Lambda max (λ_{max}) value which should equal to the number of factors in the comparison n for total consistency as given in Equation (4.8).

$$\lambda_{max} = \sum_{i=1}^n \left(\sum_{j=1}^n a_{ij} \right) w_j \quad (4.8)$$

Step 4: Calculate the Consistency Index (CI) measures as given in Equation (4.9).

$$CI = \frac{\lambda_{Max} - n}{n - 1} \quad (4.9)$$

Step 5: Calculate a Consistency Ratio (CR). If the CR is less than 0.10 (CR<0.1), then the ratio shows an acceptable level of consistency in the PCs. If CR is more than 0.10 (CR>0.1), the ratio is inconsistent as given in Equation (4.10).

$$CR = \frac{CI}{RI} < 0.1 \sim 10\% \quad (4.10)$$

With Random Index (RI) as given in Table 4.11.

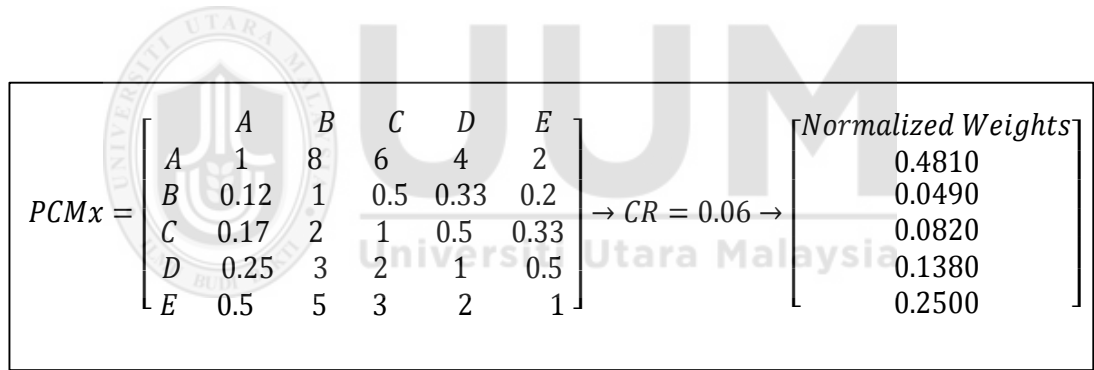
Table 4.11

Random Index

No. of Criteria	1	2	3	4	5	6	7	8	9	10	11
R. I.	0	0	0.52	0.89	1.11	1.25	1.35	1.40	1.45	1.49	1.52

In this study, the input data were collected from a set of questionnaires. The participants were asked to give importance based on Saaty Scale 1 – 9 through the comparison in between criteria. Furthermore, all the participants were assumed to have a reasonable knowledge of the e-learning criteria and alternatives. The CR value for each pairwise matrix was computed with the support of the BPMSG software (Business Performance Management Singapore). In this study, the matrices of PCs were ninety-five matrices, eighty-three of them produced consistency, and twelve matrices of them were inconsistent (see Appendix E).

For example, the evaluation and the calculation of weights from the first respondent of the administrative group and normalized weights are shown in Figure 4.3.



$$PCMx = \begin{bmatrix} & A & B & C & D & E \\ A & 1 & 8 & 6 & 4 & 2 \\ B & 0.12 & 1 & 0.5 & 0.33 & 0.2 \\ C & 0.17 & 2 & 1 & 0.5 & 0.33 \\ D & 0.25 & 3 & 2 & 1 & 0.5 \\ E & 0.5 & 5 & 3 & 2 & 1 \end{bmatrix} \rightarrow CR = 0.06 \rightarrow \begin{bmatrix} \text{Normalized Weights} \\ 0.4810 \\ 0.0490 \\ 0.0820 \\ 0.1380 \\ 0.2500 \end{bmatrix}$$

Figure 4.3. Normalized weights by PCs method

The PCs is an important phase in AHP to be completed by the experts. Nevertheless, AHP is widely criticized for being such a tedious process, especially when there is a significant number of attributes or alternatives. Some researchers may have doubted the experts' judgments because people are expected to feel tired and lose patience during this long process and thus, they may not make their decisions carefully. They may change their minds very frequently to determine the acceptance of the CR as well as to shorten the whole process. Therefore, in this study, proposed TROI

method was presented to address inconsistency problems as discussed in Chapter Five.

4.8 The Evaluation E-Learning Approaches by TOPSIS Technique

TOPSIS technique is based on the concept that rank alternatives, which has the shortest distance from the ideal. A series of steps of TOPSIS procedures are described as follows.

Step 1: Determine weights of criteria. In this study, the best criteria weights were used in the TOPSIS method. The best weights were identified by comparing each set of weights from nine sets of weights methods (ROC, RE, RR, RS, RM, RW, DPA, GW, and PCs) to the average weights of the nine methods. The weights that have the least absolute difference were considered as the best criteria weights.

Step 2: Construct a Decision Matrix (DMx), which consists of an arrangement of preferences of DMs for each alternative under each criterion. The DMx is displayed as in the following Figure 4.4.

$$DMx = \begin{bmatrix} & C_1 & C_2 & \cdots & C_n \\ A_1 & X_{11} & X_{12} & \cdots & X_{1n} \\ A_2 & X_{21} & X_{22} & \cdots & X_{2n} \\ \vdots & \vdots & \vdots & & \vdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A_m & X_{m1} & X_{m2} & & X_{mn} \end{bmatrix}$$

Figure 4.4. The decision matrix

The elements $A_1, A_2, \dots, A_m$ refer to the alternatives: while $C_1, C_2, \dots, C_n$ refer to the criteria. The elements of the DMx are related to the values of alternatives j with respect to criteria i . Where i is the criterion index $i = 1 \dots n$, and j is the alternative index $j = 1 \dots m$.

Step 3: Calculate a Normalized Decision Matrix (NDMx) by using Equation (4.11) which denotes the relative performance of the generated design alternatives.

$$NDMx = [r_{ij}]_{m \times n}, \text{ and } r_{ij} = \frac{X_{ij}}{\sqrt{\sum X_{ij}^2}}, (1 \leq i \leq n, 1 \leq j \leq m) \quad (4.11)$$

Step 4: Construct decision matrix of standardized weights by multiplying criteria weight to each element in DMx. The weighted normalized value v_{ij} is calculated as given in Equation (4.12).

$$v_{ij} = w_j \times r_{ij}, (1 \leq i \leq m, 1 \leq j \leq n) \quad (4.12)$$

Where w_j is the weight of the j^{th} criterion.

Step 5: Determine Positive Ideal Solution (A^*) and Negative Ideal Solution (A^-) as shown in Equations (4.13) and (4.14).

$$A^* = \{v_1^*, v_2^*, \dots, v_n^*\}$$

$$A^* = \left\{ \left(\max_i v_{ij} \mid i \in I' \right), \left(\min_i v_{ij} \mid i \in I'' \right) \right\} \quad (4.13)$$

$$A^- = \{v_1^-, v_2^-, \dots, v_n^-\}$$

$$A^- = \left\{ \left(\min_i v_{ij} \mid i \in I' \right), \left(\max_i v_{ij} \mid i \in I'' \right) \right\} \quad (4.14)$$

Where I' is associated with benefit criteria, and I'' is associated with cost criteria.

The TOPSIS technique usually deals with benefit and cost data. In this step, the Positive Ideal Solution (PIS) is the one with the lowest cost and has the most benefits of all alternatives, the Negative Ideal Solution (NIS) is the one with the highest cost and lowest benefits of all alternatives. In this study, all data are concerning of profit or benefit type where higher is better, but when it is a loss, the lower is the better.

Step 6: Determine separation (S_i^*) from PIS, and separation (S_i^-) from NIS, by using the m -dimensional Euclidean distance as given in Equations (4.15) and (4.16).

$$S_i^* = \sqrt{\sum_{j=1}^n (A_j^* - v_{ij})^2} \quad , i = 1, 2, \dots, m \quad (4.15)$$

$$S_i^- = \sqrt{\sum_{j=1}^n (A_j^- - v_{ij})^2} \quad , i = 1, 2, \dots, m \quad (4.16)$$

Step 7: Determine Relative Closeness (RC_i^*) to the PIS and rank the performance order as given in Equation (4.17).

$$RC_i^* = \frac{S_i^-}{S_i^* + S_i^-} \quad , i = 1, 2, \dots, m \quad (4.17)$$

Where the RC_i^* index value lies between 0 and 1. The larger the index value means the better the performance of the alternative.

For example, the following decision matrix in Table 4.12, displays the average of the judgments for each alternative given by 22 participants from the administrative group

in this study on the five e-learning approaches. Let the criteria weights are:

$C_1=0.2647$, $C_2=0.1424$, $C_3=0.1349$, $C_4=0.2761$, and $C_5=0.1819$.

Table 4.12

Decision Matrix Average

Alternatives	C_1	C_2	C_3	C_4	C_5
Blended learning	74	78	74	75	74
ICT & f-to-f learning	65	62	62	60	60
Flipped learning	83	83	80	84	85
Synchronous learning	40	39	42	38	42
Asynchronous learning	29	26	30	24	29

TOPSIS procedure consists of several steps as disclosed in Table 4.13 to 4.14 respectively.

Table 4.13

The First Part of TOPSIS Technique in Step 3

Alternatives	x_{ij}^2				
	C_1	C_2	C_3	C_4	C_5
Blended learning	5476	6084	5476	5625	5476
ICT & f-to-f learning	4225	3844	3844	3600	3600
Flipped learning	6889	6889	6400	7056	7225
Synchronous learning	1600	1521	1764	1444	1764
Asynchronous learning	841	676	900	576	841
Σx_{ij}^2	19031	19014	18384	18301	18906
$(\Sigma x^2)^{1/2}$	137.953	137.891	135.588	135.281	137.499

Based on Equation (4.11), the procedure of TOPSIS technique is shown in Table 4.14.

Table 4.14

The Second Part of TOPSIS Technique in step 3

Alternatives	C_1	C_2	C_3	C_4	C_5
Blended learning	39.695	44.122	40.387	41.580	39.826
ICT & f-to-f learning	30.626	27.877	28.351	26.611	26.182
Flipped learning	49.937	49.960	47.202	52.158	52.546
Synchronous learning	11.598	11.030	13.010	10.674	12.829
Asynchronous learning	6.096	4.902	6.638	4.258	6.116

Based on Equation (4.12), the Table 4.15 displays the procedure of TOPSIS technique.

Table 4.15

Procedure of TOPSIS Technique in Step 4

Alternatives	C_1	C_2	C_3	C_4	C_5
Blended learning	10.507	6.283	5.448	11.480	7.244
ICT & f-to-f learning	8.107	3.970	3.825	7.347	4.763
Flipped learning	13.218	7.114	6.368	14.401	9.558
Synchronous learning	3.070	1.571	1.755	2.947	2.334
Asynchronous learning	1.614	0.698	0.895	1.176	1.113

Most of the researchers use TOPSIS technique with objective weighting methods involving cost and benefit. In this study, all criteria about e-learning were benefited criteria. That is why the positive ideal solution is the maximum (max) value, whereas the negative ideal solution is the minimum (min) value. The process was carried out by taking maximum values from each column as PIS, and once again taking minimum values from each column as NIS. Based on Table 4.15, the PIS values are

$A^* = \{13.218, 7.114, 6.368, 14.401, 9.558\}$, and the NIS values are $A^- = \{1.614, 0.698, 0.895, 1.176, 1.113\}$.

The separations from the PIS and NIS based on Equations (4.15) and (4.16) are shown in Table 3.16, as well as the results of the ranking of approaches is derived using RC_i^* as in Equation (4.17).

Table 4.16

The Results of the Ranking

Alternatives	S_i^*	S_i^-	$S_i^* + S_i^-$	RC_i^*	Rank
Blended learning	4.772	16.576	21.348	0.776	2
ICT & f-to-f learning	10.734	10.623	21.357	0.497	3
Flipped learning	0	21.260	21.260	1	1
Synchronous learning	18.395	2.872	21.267	0.135	4
Asynchronous learning	21.260	0	21.260	0	5

The alternative at first rank is considered as the best maximization of expected benefits of e-learning.

As seen, from the Table 4.16 above, the results based on the TOPSIS analysis found that the flipped classroom approach of this example becomes the main priority e-learning. The second one is a blended learning approach and followed by ICT supported face-to-face learning, synchronous, and asynchronous learning.

4.9 Summary

This chapter discussed the methodology on decision framework for selecting the optimal weighting method among nine different subjective weighting methods. Since the decision framework is implemented in deciding the criteria weights of e-learning

in order to be used for evaluating five e-learning approaches. It is intended to show the implementation by illuminating all the processes involved in the research. The methodology for evaluation on five e-learning criteria has been explained in details, nine methods of subjective weights methods were compared, and the most accurate set of weights for criteria were used to evaluate five e-learning approaches by using TOPSIS method.

The following chapter presents how the proposed TROI method addresses inconsistency problem in PCs. Besides that, an example of the application of the proposed TROI method in solving different cases of inconsistency is also provided. In doing so, the proposed method works as a general method since it can deal with various judgments of inconsistency.



CHAPTER FIVE

THE PROPOSED TROI METHOD

This chapter describes the proposed Tripartite Relations for Overcoming Inconsistency (TROI) method and the steps of applying it to address inconsistency problems in pairwise comparisons (PCs) technique. First, Section 5.1 briefly describes inconsistency indicators in PCs and some related literature. Next, introduction to TROI method is presented in Section 5.2. Section 5.3 discusses how proposed TROI method can be used to resolve inconsistent pairwise comparison matrix. The algorithm of the proposed TROI method is described in Section 5.4. Then, the detail procedure of TROI method has been explained in Section 5.5, as well as the illustrative example of the implementation of the TROI method is observed in Section 5.6. Section 5.7 offers a new proposed pairwise comparison approach based on the proposed TROI method. Finally, the summary of this chapter is presented in Section 5.8 at the end of the chapter.

5.1 Inconsistency Indicators in PCs

There are different reasons that lead to inconsistent judgments in PCs including psychological causes, an insufficient model structure and clerical errors (Sugden, 1985). The psychological causes may lead to uncertainty, incomplete information and lack of attention or concentration through the judgment process. Another reason may affect the judgment is the incorrect data entry which leads to lack of understanding of the issue, and the Decision Maker (DM) will give judgment incorrectly.

The main cause of inconsistency is the Saaty scale for decisions, the 1 – 9 scale (Saaty, 1980). Suppose that if the judgment for A is 6 times better than B and the judgment for B is 5 times better than C, so the real value between A to C is more than 9, and this value is not allowed when utilizing 1 – 9 scale. In other words, according to Saaty, suppose $a_{AB}=3$ and $a_{BC}=2$, then for a perfect consistency, $a_{AC}=6$ ($a_{AC} = a_{AB} \times a_{BC}$). Furthermore, if $a_{AB}=4$ and $a_{BC}=5$, then to get a perfect consistency, a_{AC} should be 20, and this value is also not allowed in Saaty's scale since the largest value is set at 9. Therefore, Saaty's approach allows for some inconsistencies.

In fact, in PCs method, the number of comparisons is increasing as the number of criteria increases. Therefore, a large number of criteria may lead to inconsistent judgments, and these judgments may need to be revised by DM several times.

Furthermore, the following sections discuss the TROI method as a proposed method for processing inconsistency judgments in PCs method. Basically, TROI method keeps the first row of the inconsistent matrix, while the rest of the rows of that matrix are deleted. Then, TROI method offers a procedure to generate the elements of row two and onwards based on the first row of the inconsistent PC matrix.

5.2 Introduction to Proposed TROI Method

In a view to overcome inconsistency problem in PCs method without the need of revised judgments from DM, the tripartite relations (for instance, $A \leftrightarrow B$ compared with $A \leftrightarrow C$, to get $B \leftrightarrow C$) have been used among criteria to overcome that problem of inconsistency in order to get logical judgments, as well as to facilitate the task of the

researchers. The improvements can be made manually without asking DM to revise the judgments, using an improved technique for tripartite relations among criteria.

The idea of TROI method came out from Rational Choice Theory. The Rational Choice Theory of stakeholders' behavior depends on the following axioms regarding stakeholders' preferences.

- I. For any pair of options (A and B), the stakeholder either prefers A to B, prefers B to A (The DM will choose the most preferred option), or is indifferent in between A and B. This is the axiom of completeness.
- II. These preferences (choices) are transitive. That is if a DM prefers A to B, and also B to C, then necessarily DM prefers A to C. If DM is indifferent between A and B, and also between B and C, then DM is necessarily indifferent between A and C.

An ordinal consistency is also known as the “transitivity” condition among three elements, that states that if C_1 is preferred to C_2 and C_2 is preferred to C_3 , then C_1 should be preferred to C_3 (If $C_1 \rightarrow C_2 \rightarrow C_3$ then $C_1 \rightarrow C_3$). The preference dominance is easy to depict, where the transitive relationship is represented as a cycle among those three elements (Siraj, Mikhailov, & Keane, 2015). The ordinal inconsistent (intransitive) or preference judgments are if C_3 is preferred to C_1 when C_1 is preferred to C_2 and C_3 ($C_3 \rightarrow C_1$ when $C_1 \rightarrow C_2 \rightarrow C_3$). Therefore, the ordinal inconsistency can be defined as $C_1 \rightarrow C_2 \rightarrow C_3 \rightarrow C_1$, which represents a three-way cycle or a circular triad of preferences (Kendall, 1955). This relation means that the judgment between each row elements satisfies the inequality $a_{ij} > 1$. Thus, the ordinal inconsistency implies that the corresponding judgments are $a_{ij} > 1$, $a_{jk} >$

1 and $a_{ki} > 1$. This means that a judgment $a_{ik} > 1$ will introduce ordinal inconsistency (Jensen & Hicks, 1993).

If the judgments in PCs are ordinal inconsistent (intransitive), it is not potential to find a priority vector, and consequently, there will always be priority violations. Therefore, different techniques about the problem of ordinal inconsistency have been introduced to detect and rectify inconsistent judgments. (Ahn & Park, 2008; Brunelli, 2016; Cao, Leung, & Law, 2008; Gass, 1998; Holsztyński & Koczkodaj, 1996; Siraj, 2015; Zeshui & Cuiping, 1999).

Cardinal consistency, which is a much stronger requirement than ordinal consistency, states that if A is preferred to B x times, and B is preferred to C y times, then A should be preferred to C $x.y$ times. The AHP does not require transitivity of DM's judgments (Siraj, Mikhailov, & Keane, 2012). Saaty's Consistency Ratio (CR) index measures the cardinal inconsistency of the judgments but does not capture their ordinal inconsistency. If the CR is less than 0.10 ($CR < 0.1$), then the ratio shows an acceptable level of consistency in the PCs. Ordinal inconsistency always implies cardinal inconsistency, however, the converse does not hold. Generally, if the comparison judgments and the corresponding PC matrix are ordinal inconsistent, the value of CR is above the threshold of 0.1. Therefore, the AHP implicitly presumes that satisfying the CR test may significantly reduce the chances of ordinal inconsistency. However, there are examples in the literature where matrices that satisfy the CR criterion can also be ordinal inconsistent (Jensen & Hicks, 1993; Kwiesielewicz & van Uden, 2004).

In this study, the new proposed TROI method is introduced to rectify inconsistency judgments in PCs technique whether ordinal inconsistency or cardinal inconsistency, as well as it aims to reduce the number of comparisons.

5.3 How Proposed TROI Method Can Be Used to Resolve Inconsistent Pairwise Comparison Matrix

As mentioned earlier, in order to address inconsistent judgments, TROI method keeps the first row of the inconsistent PC matrix. The elements of the first row are assumed to represent correct decisions (constants), and the rest of elements would represent incorrect judgments. However, the elements in the first row may change if the sum of the comparison elements is more than nine. The details are explained in Section 5.5. The wrong judgments in the matrix should be changed, based on the right judgments in the first row by using TROI formulas.

For instance, if there is an inconsistent PC matrix, then all the judgments in the matrix should be deleted except for the first row elements as shown in Figure 5.1.

$$J = \begin{bmatrix} & A & B & C & D \\ A & 1 & 1/8 & 1/2 & 6 \\ B & & 1 & 7 & 9 \\ C & & & 1 & 2 \\ D & & & & 1 \end{bmatrix} \rightarrow CR = 0.15 \rightarrow \begin{bmatrix} & A & B & C & D \\ A & 1 & 1/8 & 1/2 & 6 \\ B & & 1 & ? & ? \\ C & & & 1 & ? \\ D & & & & 1 \end{bmatrix}$$

Figure 5.1. Deleting judgments in all rows except row 1 in inconsistent PC matrix

The elements in the first row are produced from comparisons between the first item with the others ($A \rightarrow B$, $A \rightarrow C$, and $A \rightarrow D$). Those comparisons are enough to elicit the rest of judgments correctly, as well as leading to consistent judgments for the

whole matrix automatically. The new judgments are extracted through the comparisons between the elements in the first row, and that means the second element (a_{12}) compares with others ($a_{13}, a_{14}, \dots, a_{1n}$), the third element (a_{13}) compares with others ($a_{14}, a_{15}, \dots, a_{1n}$), and so on as shown below based on the example above as in Figure 5.1. Please note, the first element in row one, (a_{11}) is located in the diagonal of PC matrix, where its value is always equal to one. Therefore, this element is not used in TROI method. Furthermore, the following procedures address how to get the entries of the PC matrix in row two, three and so on based on entries in row one.

- I. Procedure 1: Compare a_{12} with a_{13} to get new judgment for a_{23}
- II. Procedure 2: Compare a_{12} with a_{14} to get new judgment for a_{24}
- III. Procedure 3: Compare a_{13} with a_{14} to get new judgment for a_{34}

The first procedure means that the entry or element located at row one and column two of PC matrix is compared with the entry located at row one and column three to get a new judgment for entry at row two and column three. The second and third procedures follow the same type of actions. Entries in row one together with the three new entries that will be obtained based on procedures (I, II, and III) would make up the complete upper triangular part of PC matrix. The lower triangular part of the matrix would be obtained from the reciprocal of the entries of the upper triangular part.

After that, the new matrix will consist of new judgments as well as the original first row. The comparisons between elements in the first row are based on the rationality. In general, for a PC matrix of size $n \times n$, the DM is asked to choose the most

preferred option in between each two criteria or alternatives based on the first item (criterion or alternative) in the first row in PC matrix. For instance, $A \rightarrow B, A \rightarrow C, \dots, A \rightarrow n$, where A is the first item, and n is the number of items.

For example, it can be assumed that if A is three times more important than B ($a_{12} = 3$), and A is five times more important than C ($a_{13} = 5$), then the relation between B and C will be under some considerations. The value of items should be checked, if the first item greater or less than the next item ($a_{12} > a_{13}$ or $a_{12} < a_{13}$). Here, the value of a_{12} is less than the value of a_{13} , then should find a_{23} value by taking absolute value in between first and next items with plus one, and the result of this example is three ($a_{23} = 3$). In this process, one (1) should be added to avoid zero (0) when we have two equal values, and it should be based on Saaty scale (1-9). The details in the following sections.

5.4 Algorithm of the Proposed TROI Method

This section summarizes the steps of TROI method. The general steps of the proposed TROI method can be summarized as an algorithm as follows:

Step 1: Keep the elements of the first row in the inconsistent PC matrix, and ignore the rest of the rows. However, some elements in the first row may change if the sum of comparison elements is greater than nine (the details are in case 2 and 3 in the next section). In other words, the sum of the two comparative elements in row one as in case 2 and 3 should be checked as to whether it is equivalent to more or less than nine.

Step 2: Determine the type of each element in the first row of PC matrix whether it is Integer element (*In*) or Fractional element (*Fr*).

Step 3: Compare the elements in the first row based on the following cases:

Case1: (*In*) with (*In*).

Case 2: (*In*) with (*Fr*).

Case 3: (*Fr*) with (*In*).

Case 4: (*Fr*) with (*Fr*).

Step 4: Fill all rows of the PC matrix except row one with new values (judgments) which are obtained from the comparisons.

Step 5: Check the consistency of the corrected matrix.

The details and steps of this algorithm are presented in the next sections.

5.5 The Details of the TROI Algorithm

A series in steps of TROI procedures is described as follows:

Step 1: Determine the elements of the first row in the inconsistent judgments matrix.

Let J is $n \times n$ PC matrix (see Figure 5.2) with the rows $i = 1, 2, \dots, n$ and columns $j = 1, 2, \dots, n$.

$$J = \begin{bmatrix} 1 & a_{12} & \dots & a_{1n} \\ a_{21} & 1 & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{bmatrix}$$

Figure 5.2. The decision matrix in PCs method

Let $i = 1$, for $j = 2, 3, \dots, n$, and loop $j = j + 1, \dots, n$.

Step 2: Determine the type of elements in the first row, whether Integer or Fractional elements (*In* and *Fr*) in the first row given by the evaluators. For example, if $a_{12} = 3$ that means this element is *In*, while if $a_{12} = \frac{1}{3}$ that means this element is *Fr*.

Step 3: Make comparison of the elements in the first row. The relationship between each two elements are created based on the following cases:

Case 1. *In* (a_{1j}) with *In* ($a_{1,j+1}$). Please note that $a_{1,j+1}$ represents the element located at row 1 and column $j+1$.

- If $a_{1j} > a_{1,j+1} \rightarrow$ then calculating the new element a_{kt} by Equation (5.1)

$$a_{kt} = |a_{1j} - a_{1,j+1}| + 1 \quad (5.1)$$

Where $k = j + 1$, and $t = j$

- If $a_{1j} < a_{1,j+1} \rightarrow$ then calculating the new element a_{xy} by Equation (5.2)

$$a_{xy} = |a_{1j} - a_{1,j+1}| + 1 \quad (5.2)$$

Where $x = j$, and $y = j + 1$

Case 2. *In* (a_{1j}) with *Fr* ($a_{1,j+1}$). Do swap for *Fr* element $a_{1,j+1} \rightleftharpoons a_{j+1,1}$ then

- If $(a_{1j} + a_{j+1,1}) \leq 9$, then calculate the new element a_{zf} . Please note that if the sum of elements is less than nine that means these elements in the first row are consistent, then Equation (5.3) can be used to get the new element.

$$a_{zf} = a_{1j} + a_{j+1,1} \quad (5.3)$$

Where $z = j + 1$, and $f = j$

- If $(a_{1j} + a_{j+1,1}) > 9$, then change these elements. Please note that if the sum of elements is greater than nine that means these elements (a_{1j} and $a_{j+1,1}$) in the first row are inconsistent, then should be changed by using Equations (5.4) – (5.6) to get new elements in the first row.

$$e = a_{1j} + a_{j+1,1} - 9 \quad (5.4)$$

$$\text{new } a_{1j} = a_{1j} - e \quad (5.5)$$

$$\text{new } a_{j+1,1} = a_{j+1,1} - e \quad (5.6)$$

If the comparison elements (*In* with *Fr*) in case 2 is greater than nine, then a_{1j} and $a_{j+1,1}$ should be changed to get new elements. After getting new elements in row one, then the comparisons between the elements in row one has to be repeated.

Case 3. *Fr* (a_{1j}) with *In* ($a_{1,j+1}$). Do swap for $Fr\ a_{1j} \rightleftharpoons a_{j1}$ then

- If $(a_{j1} + a_{1,j+1}) \leq 9$, then calculate the new element a_{sm} . Please note that if the sum of elements is less than nine that means these elements in row one are consistent, then Equation (5.7) can be used to get the new element.

$$a_{sm} = a_{j1} + a_{1,j+1} \quad (5.7)$$

Where $s = j$, and $m = j + 1$

- If $(a_{j1} + a_{1,j+1}) > 9$, then change these elements (a_{j1} and $a_{1,j+1}$). Please note that if the sum of the elements (a_{j1} and $a_{1,j+1}$) is greater than nine that means these elements in row one are inconsistent, then a_{j1} and $a_{1,j+1}$ should be changed by using Equations (5.8) – (5.10) to get new elements in the first row.

$$e = a_{j1} + a_{1,j+1} - 9 \quad (5.8)$$

$$new\ a_{j1} = a_{j1} - e \quad (5.9)$$

$$new\ a_{1,j+1} = a_{1,j+1} - e \quad (5.10)$$

If the comparison in between *Fr* and *In* (case 3) produces greater than nine, then those elements (a_{j1} and $a_{1,j+1}$) should be changed to get new elements in row one. After getting new elements in row one, then the comparisons between the elements in row one has to be repeated.

Note: If the sum of elements is greater than nine (as in case 2 and 3) and this situation may recur more than once in row one, then the larger value should be selected and changing related elements. For example, if there are several comparisons (In and Fr, or Fr and In) and their results are greater than 9 (e.g. $a_{12} + a_{13} = 10$, $a_{12} + a_{14} = 12$, and $a_{12} + a_{15} = 14$) then the largest value, which is 14 should be selected and change the related elements (a_{12} and a_{15}), to get the new elements in the first row and repeat the process from the beginning.

Case 4. *Fr* (a_{1j}) with *Fr* ($a_{1,j+1}$). Do swap two times, once for first element $a_{1j} \rightleftharpoons a_{j1}$ and once again for next element $a_{1,j+1} \rightleftharpoons a_{j+1,1}$, then

- If $a_{j1} > a_{j+1,1} \rightarrow$ then calculate the new element a_{cd} by Equation (5.11)

$$a_{cd} = |a_{j1} - a_{j+1,1}| + 1 \quad (5.11)$$

Where $c = j$, and $d = j + 1$

- If $a_{j1} < a_{j+1,1} \rightarrow$ then calculate the new element a_{bh} by Equation (5.12).

$$a_{bh} = |a_{j1} - a_{j+1,1}| + 1 \quad (5.12)$$

Where $b = j + 1$, and $h = j$

Step 4: Fill the matrix by new judgments which are obtained from the comparisons based on the TROI Equations (5.1) – (5.12) as well as taking reciprocal for each new element, $a_{ji} = 1/a_{ij}$. For example, if the new element is $a_{23} = 2$ then the reciprocal

for this element is $a_{32} = \frac{1}{2}$ and so on for the rest of the matrix. Here, the use of TROI Equations (5.1) – (5.12) would produce a complete upper triangular of PC matrix. So the rest of the elements in the lower triangular part of the PC matrix are also determined by taking the reciprocal of each element in the upper triangular part of PC matrix. This process is repeated for the rest of the matrix. As a result, a complete new PC matrix is produced.

Step 5: Check the Consistency Ratio (CR) of the corrected matrix. The CR checking is conducted as what is done for AHP method.

5.6 Illustrative Example

The matrix in Figure 5.3 contains the judgments from one of the participants in academic staff group (refer to Appendix E, P4). The judgments were inconsistent with CR=0.423, then it should be addressed and corrected by the proposed TROI method. This example has all cases based on TROI formulas. The details and steps regarding this example are presented as follows:

$$J = \begin{bmatrix} & A & B & C & D & E \\ A & 1 & 2 & 1/2 & 1/3 & 3 \\ B & & 1 & 1/3 & 1/5 & 2 \\ C & & & 1 & 1/2 & 1/6 \\ D & & & & 1 & 8 \\ E & & & & & 1 \end{bmatrix} \rightarrow CR = 0.42$$

Figure 5.3. An example of inconsistent PC matrix

Step 1: Determine the type of elements in the first row based on which one is *In*, and also which one is *Fr*, as follows:

$$a_{12} = 2 \rightarrow In$$

$$a_{13} = \frac{1}{2} \rightarrow Fr$$

$$a_{14} = \frac{1}{3} \rightarrow Fr$$

$$a_{15} = 3 \rightarrow In$$

Step 2: Make comparisons between the elements only in the first row as follows:

$$a_{12} \text{ with } a_{13}$$

$$a_{12} \text{ with } a_{14}$$

$$a_{12} \text{ with } a_{15}$$

$$a_{13} \text{ with } a_{14}$$

$$a_{13} \text{ with } a_{15}$$

$$a_{14} \text{ with } a_{15}$$

Note: Make sure that the comparisons are made in one way, but not two ways $\nleftrightarrow$.

Step 3: Apply the formulas (5.1) – (5.12), where applicable, through comparison in between each two elements in the first row, except the first element of row one (a_{11}), based on TROI formulas as follows:

➤ *In* with *Fr* (a_{12} with a_{13}), $a_{12} = 2 \rightarrow In$ is compared with $a_{13} = \frac{1}{2} \rightarrow Fr$.

Based on case 2 with Equation (4.3) the new element is calculated as follows:

Do swap for *Fr* element $a_{13} = \frac{1}{2} \Leftrightarrow a_{31} = 2$ then check $a_{12} + a_{31} \leq 9$ (refer to the note in case 2).

$$\text{Sum } (2 + 2) = 4 < 9$$

Based on Equation (4.3), the new element is a_{32} as follows:

$$a_{32} = a_{12} + a_{31}$$

$$a_{32} = 2 + 2 = 4$$

➤ *In* with *Fr* (a_{12} with a_{14}), $a_{12} = 2 \rightarrow In$ compared with $a_{14} = \frac{1}{3} \rightarrow Fr$.

Based on case 2 with Equation (5.3) the new element is calculated as follows:

Do swap for *Fr*, $a_{14} = \frac{1}{3} \Leftrightarrow a_{41} = 3$ then check $a_{12} + a_{41} \leq 9$ (refer to the note in case 2).

$$\text{Sum } (2 + 3) = 5 < 9$$

Based on Equation (5.3), the new element is a_{42} as follows:

$$a_{42} = a_{12} + a_{41}$$

$$a_{42} = 2 + 3 = 5$$

➤ *In* with *In* (a_{12} with a_{15}), $a_{12} = 2 \rightarrow In$ compared with $a_{15} = 3 \rightarrow In$.

Based on case 1 with Equation (5.2), $a_{12} < a_{15}$ ($2 < 3$) then the new element a_{25} is calculated as follows:

$$a_{25} = |a_{12} - a_{15}| + 1$$

$$a_{25} = |2 - 3| + 1 = 2$$

➤ *Fr* with *Fr* (a_{13} with a_{14}), $a_{13} = \frac{1}{2} \rightarrow Fr$ compared with $a_{14} = \frac{1}{3} \rightarrow Fr$.

Based on case 4 with Equation (5.12) the new element is calculated as follows:

Do swap for *Fr* element $a_{13} = \frac{1}{2} \Leftrightarrow a_{31} = 2$ and once again do swap for *Fr*

element $a_{14} = \frac{1}{3} \Leftrightarrow a_{41} = 3$, so $a_{31} < a_{41}$ ($2 < 3$), then based on

Equation (5.12), the new element a_{43} is calculated as follows:

$$a_{43} = |a_{31} - a_{41}| + 1$$

$$a_{43} = |2 - 3| + 1 = 2$$

➤ *Fr* with *In* (a_{13} with a_{15}), $a_{13} = \frac{1}{2} \rightarrow Fr$ compared with $a_{15} = 3 \rightarrow In$.

Based on case 3 with Equation (5.7) the new element is calculated as follows:

Do swap for *Fr* element $a_{13} = \frac{1}{2} \Leftrightarrow a_{31} = 2$ then check $a_{31} + a_{15} \leq 9$
(refer to the note in case 3).

$$2 + 3 = 5 < 9$$

Then the new element a_{35} is calculated as follows:

$$a_{35} = a_{31} + a_{15}$$

$$a_{35} = 2 + 3 = 5$$

➤ *Fr* with *In* (a_{14} with a_{15}), $a_{14} = \frac{1}{3} \rightarrow$ *Fr* compared with $a_{15} = 3 \rightarrow$ *In*.

Based on case 3 with Equation (5.7) the new element is calculated as follows:

Do swap for *Fr* element $a_{14} = \frac{1}{3} \Leftrightarrow a_{41} = 3$ then check $a_{41} + a_{15} \leq 9$
(refer to the note in case 3).

$$3 + 3 = 6 < 9, \text{ then}$$

$$a_{45} = a_{41} + a_{15}$$

$$a_{45} = 3 + 3 = 6$$

Step 4: After all comparisons among the elements based on the first row elements are made, arrange the new elements values in all rows of the upper triangular part of the matrix, as well as the corresponding reciprocal in the lower triangular part of the

matrix. For instance, the comparison in between a_{12} and a_{13} produced $a_{32} = 4$ and the reciprocal for this element is $a_{23} = \frac{1}{4}$ as described below:

$$a_{12} \text{ with } a_{31} \rightarrow a_{32} = 4, \text{ and reciprocal is } a_{23} = \frac{1}{4}$$

$$a_{12} \text{ with } a_{41} \rightarrow a_{42} = 5, \text{ and reciprocal is } a_{24} = \frac{1}{5}$$

$$a_{12} \text{ with } a_{15} \rightarrow a_{25} = 2, \text{ and reciprocal is } a_{52} = \frac{1}{2}$$

$$a_{31} \text{ with } a_{41} \rightarrow a_{43} = 2, \text{ and reciprocal is } a_{34} = \frac{1}{2}$$

$$a_{31} \text{ with } a_{15} \rightarrow a_{35} = 5, \text{ and reciprocal is } a_{53} = \frac{1}{5}$$

$$a_{41} \text{ with } a_{15} \rightarrow a_{45} = 6, \text{ and reciprocal is } a_{54} = \frac{1}{6}$$

Based on the comparisons among the elements in the first row, a new PC matrix is produced as shown in the new matrix (see Figure 5.4).

$$J = \begin{bmatrix} & A & B & C & D & E \\ A & 1 & 2 & 1/2 & 1/3 & 3 \\ B & & 1 & 1/4 & 1/5 & 2 \\ C & & & 1 & 1/2 & 5 \\ D & & & & 1 & 6 \\ E & & & & & 1 \end{bmatrix} \rightarrow \text{CR} = 1.2\%$$

Figure 5.4. The corrected matrix

Based on the Figure 5.4, it can be seen that the new matrix after correction of judgments, the CR is 1.2%, and this is less than 10%. While the original matrix was inconsistent with CR = 42%, and this value is more than 10%. Overall, the new matrix with corrected judgments in PC matrix by using TROI method will always be consistent.

5.7 New PCs Procedure Based on TROI Algorithm (PC-TROI)

In the AHP, pairwise judgments are structured in a PC matrix, and a prioritization procedure is applied to derive a corresponding priority vector. If the comparison judgments are cardinally consistent, then the constructed PC matrix is also consistent, and all prioritization methods will give the same result. However, in the case of ordinal or cardinal inconsistent judgments, different prioritization methods derive different priority vectors.

To fill out a PC matrix in the original PCs method, the DM makes $n(n - 1)/2$ of comparisons among items, where n refers to the number of items or criteria. For three items, it is easy to compare between them. For a larger number of items, it can become a bit more complicated, especially when six or more items are involved. Nine items is the usual upper-limit for PCs method and requires 36 comparisons (Gass, 1998). In such situations, inconsistent judgments may occur, as it is hard task for the DM to track of all the preferences. Additionally, the complexities inherent in a MCDM problem also make it difficult to accomplish an inconsistent-free PC matrix.

TROI method highlights that not only to address inconsistent indicators in PCs but also can be used to create a new process to PC based on TROI (PC-TROI) for the DM to deals with PCs easily, through reducing comparisons significantly. Based on PC-TROI procedure, DM does not need to conduct comprehensive comparisons among all the criteria. But the DM only makes $(n - 1)$ of comparisons among items by using 1 – 5 scale (see Table 5.1) rather than Saaty's scale to avoid inconsistent cases especially when dealing with large number of criteria, where n refers to the number of items or criteria.

Table 5.1

Scale of Relative Importance for Proposed TROI Method

Scale of Importance	Numeric Rating
Extreme Importance	5
Very strong Importance	4
Strong Importance	3
Moderate Importance	2
Equal Importance	1

The judgments in TROI process will be consistent automatically based on conditions in TROI formulas as mentioned previously. In this proposed PC-TROI method, a number of comparisons among items $(n - 1)$ depends on the comparison of the first item (criterion or alternative) with the other items, and this refers to elements in the first row of the matrix. For instance, if there are nine criteria, DM should make 36 of comparisons based on original PCs, while based on PC-TROI method DM should make only eight comparisons that would produce the elements of the first row of the PC matrix.

For example, if there are five criteria (A, B, C, D, and E), the number of the comparisons based on TROI method is only four. In this example, the comparison between the following criteria namely: $A \rightarrow B$, $A \rightarrow C$, $A \rightarrow D$, and $A \rightarrow E$ are required. Thus, after the evaluation of the DM on five criteria by four comparisons, the rest of the elements are produced via TROI procedures by using Equations (5.1) to (5.12). The MATLAB language program to calculate TROI procedures is available in Appendix H.

5.8 Summary

The inconsistent judgments are major problems in PCs method. In this study, this chapter provides a new characterization on how to correct the inconsistent PC matrix by proposing the TROI method. The proposed TROI method can address both types of inconsistency whether ordinal or cardinal. This proposed method enables us to check the consistency of the experts' viewpoints conveniently without the need of revised judgments from DM. Likewise, PC-TROI is a procedure to construct consistent preference relations has been presented by obtaining the elements of the first row only, and the rest of the rows are determined by comparing only the elements in the first row in PC matrix while reducing the number of comparisons significantly among criteria or alternatives. In other words, the evaluator(s) has less burden in making the pairwise comparison as compared to what they have to do in the original PCs steps. This is an attempt to find a suitable solution for inconsistent problems that are usually faced by researchers in utilizing PCs method.

The following chapter displays the results of the implementation of the proposed decision framework in the evaluation of e-learning approaches, where nine weighting methods were analyzed including PCs method for e-learning criteria evaluation and

TOPSIS method for five type of e-learning evaluation. Since AHP was used as one of the nine weighting methods, the TROI method was applied to resolve the inconsistent matrices. The results of the application of TROI are also available in the next chapter.



CHAPTER SIX

APPLICATION OF THE PROPOSED DECISION FRAMEWORK AND TROI METHOD: RESULTS AND DISCUSSION

This chapter focuses on applying the steps of the proposed decision framework in order to determine the optimal subjective weighting method which involves nine subjective weights methods for evaluating e-learning approaches. The identification of e-learning criteria is in Section 6.1. Analysis of criteria weights is presented next in Section 6.2. The results of evaluation of criteria and comparison of weights are illustrated in 6.3. Sections 6.4 displayed the best-ranked criteria weights based on the comparison among subjective weights methods. Evaluation of the five e-learning approaches using TOPSIS method is presented in Section 6.5. The validation of the results is described in Section 6.6. The discussion section is in Section 6.7. Finally, the summary of the chapter is at the end of this chapter.

6.1 Identification E-Learning Criteria

The criteria of e-learning approaches are selected based on the literature (Begičević & Divjak, 2006; Begičević et al., 2007). These criteria were used to develop a multi-criteria selection model in the case study. After short-listing the e-learning criteria, the identification of priorities ranking of these criteria was based on the respondents' preferences by using nine different subjective weighting methods. Five e-learning criteria were employed in the survey for developing their priority ranking from participants' responses. Only benefit criteria would selected in this study, the detail about the criteria are described as follows:

- I. **Human resources:** included technical support staff for e-learning, availability of support staff for the methodology of e-learning, availability of support staff for graphical design, animation and video, continuous training of academic staff and continuous training of support staff.
- II. **Specific ICT infrastructure for e-learning:** included library management system, Exam management system, Network video-conferencing system, video and audio streaming, production of video and audio materials and systems for simulation and virtual environment.
- III. **Basic ICT infrastructure for e-learning:** included Network infrastructure, Teachers and students equipped with computers, managed learning environment and Classrooms equipped for e-learning.
- IV. **Strategic readiness for e-learning implementation:** included faculty strategy for development, University framework for development and financial readiness of universities/faculties for e-learning implementation.
- V. **Legal and formal readiness for e-learning implementation:** included system and criteria for academic staff promotion and evaluation and quality control at universities/faculties.

6.2 Analysis of Criteria Weights

After determining the e-learning criteria, a priority ranking of criteria was established from the survey participants' preferences through a set of questionnaire (refer Appendices B, C, and D). The weights of the criteria were analyzed by using nine different subjective weighting methods as given in Appendix F. These methods namely: Rating (RM), Rank Order Centroid (ROC), Rank Exponent (RE), Rank Reciprocal (RR), Rank Sum (RS), Ratio (RW), Graphical Weights (GW), Direct

Point Allocation (DPA), and Pairwise Comparisons (PCs) methods. Criteria weights were calculated by MATLAB language program and the program given in Appendix G. The following nine subsections demonstrate the weighting process to obtain different sets of criteria weights by utilizing the nine different subjective weighting methods. Since the optimal or the best weights should be decided, the proposed decision framework is the best procedure to determine the optimal weights.

6.2.1 RS Method

The RS method was applied to allocate the weights for the selected criteria. The respondents were asked to rank the selected criteria from 1 to 5 as mentioned previously. Furthermore, the ranking from the respondents was also used in RR, RE, and ROC methods to identify criteria weights. In RS method, the data collected from the respondents were analyzed and divided into three groups namely: administrative (G1-RS), academic staff (G2-RS), and postgraduate students (G3-RS). Later, to aggregate the individual weights, Geometric mean (G. Mean) approach for each criterion was calculated for each group. Next, the G. mean weights were normalized by dividing each G. Mean weight with the sum of G. mean weights to guarantee that the sum of these final weights of each group is equal to one.

After that, the G-Mean was used once again to get the geometric weights for each criterion of all groups. Then the final weights of the method were normalized once again to make sure that the sum of weights is one. Summary of the normalized weights of each group and all groups for each criterion is shown in Table 6.1. The normalized weights of all groups are represented as Final Weights for RS method

(FW-RS). The weights (w_i) were calculated using RS method based on the formula in Equation (6.1) as explained in the previous chapter.

$$w_i(RS) = \frac{K - r_i + 1}{\sum_{j=1}^K K - r_i + 1} \quad (6.1)$$

Where K is the number of attributes under consideration, r_i is the rank position of the criterion i , $i = 1, \dots, K$. The weight, w_i , is the normalized weight for each criterion i (C_i).

Table 6.1

The Weights and Rank for the Criteria Using RS Method

Groups	C_1 (Rank)	C_2 (Rank)	C_3 (Rank)	C_4 (Rank)	C_5 (Rank)
G1-RS	0.2332(2)	0.1407(4)	0.1384(5)	0.2858(1)	0.2018(3)
G2-RS	0.2487(1)	0.1954(3)	0.1688(3)	0.2047(2)	0.1824(4)
G3-RS	0.2863(1)	0.1347(4)	0.1116(5)	0.2853(2)	0.1821(3)
G. Mean	0.2551	0.1547	0.1376	0.2556	0.1885
FW-RS	0.2573(2)	0.1560(4)	0.1388(5)	0.2578(1)	0.1901(3)

Through the results in Table 6.1, it can be seen that the group 2 and 3 evaluated C_1 to be most important than others, while group 1 preferred C_4 as the most important criterion than others. The Final Weights by using G. Mean for all groups in RS method (FW-RS) shows that the C_4 is the most important than others. Also, the analysis of this method is displayed in Figure 6.1.

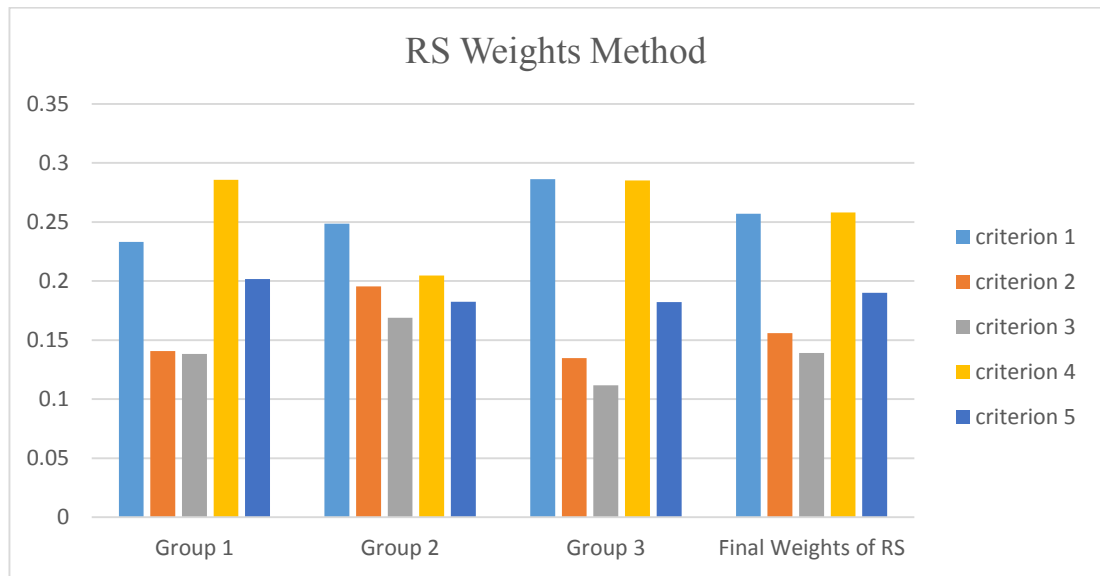


Figure 6.1. The criteria weights using RS method

6.2.2 RR Method

Based on the ranking of each criterion given by three groups of respondents, criteria weights have been calculated by using RR method of three different groups. In RR method, the data collected from the respondents were analyzed and divided into three groups namely: administrative (G1-RR), academic staff (G2-RR), and postgraduate students (G3-RR). The same processes as mentioned in RS were carried out, and the normalized weights of each group and the normalized displayed in Table 6.2. The normalized weights of all groups are displayed as Final Weights for RR method (FW-RR). The RR weights are normalized reciprocals of criteria's rank, as given in Equation (6.2).

$$w_i(RR) = \frac{1/r_i}{\sum_{j=1}^K (1/r_j)} \quad (6.2)$$

Where K is the number of criteria, r_i is the rank position of the criterion i , $i=1,\dots,K$.

The weight w_i is the normalized weight for each criterion i (C_i).

Table 6.2

The Weights and Rank for the Criteria Using RR Method

Groups	C_1 (Rank)	C_2 (Rank)	C_3 (Rank)	C_4 (Rank)	C_5 (Rank)
G1-RR	0.2197(2)	0.1376(5)	0.1459(4)	0.2841(1)	0.2127(3)
G2-RR	0.2340(1)	0.1822(5)	0.1848(4)	0.1999(2)	0.1991(3)
G3-RR	0.2867(2)	0.1282(4)	0.1175(5)	0.2994(1)	0.1682(3)
G. Mean	0.2452	0.1476	0.1469	0.2571	0.1924
FW-RR	0.2479(2)	0.1492(4)	0.1485(5)	0.2599(1)	0.1945(3)

The analysis via RR method has shown that the group 2 preferred C_1 as the most important than others. Also, through the same table, it can be seen that the group 1 and 3 preferred C_4 to be most important than others. The G. Mean for all groups has been used to produce the Final Weights as a final criteria weights of RR method (FW-RS), and its showed that the C_4 is the most important than others. Likewise, the criteria weights by using this method is displayed in Figure 6.2.

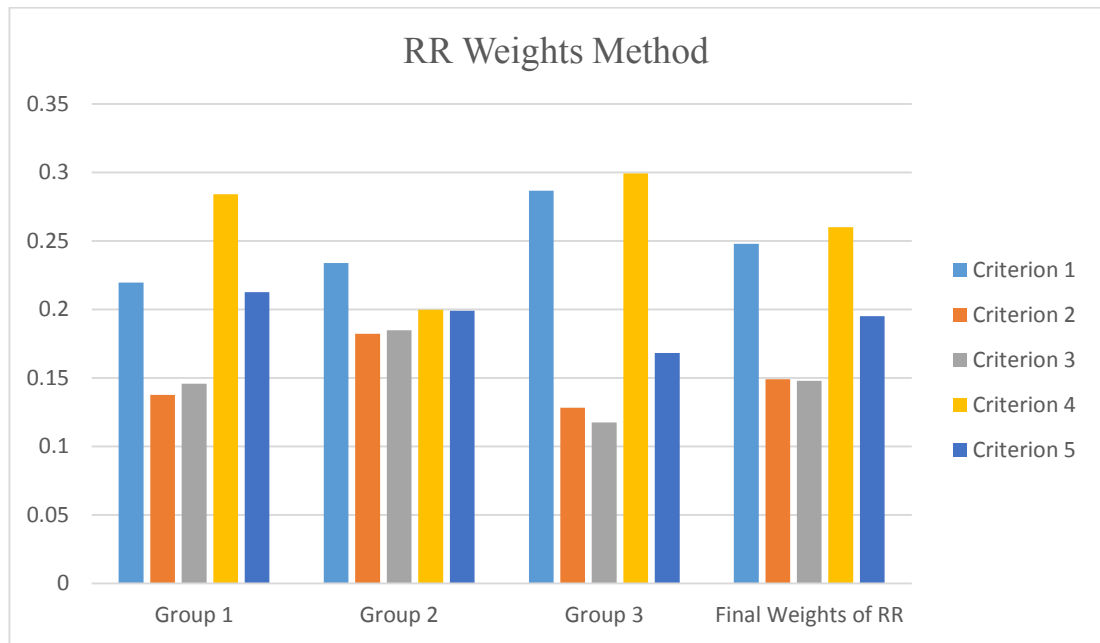


Figure 6.2. The criteria weights using RR method

6.2.3 RE Method

Similar processes were repeated as previously mentioned, but now criteria weights were calculated by using RE method. The RE method is a generalization of the RS, which is calculated as in Equation (6.3).

$$w_i(RE) = \frac{(K - r_i + 1)^p}{\sum_{j=1}^K (K - r_j + 1)^p} \quad (6.3)$$

Where r_i is the rank of the i – th criterion, K is the number of criteria, p is the parameter describing the attributes, $i = 1, 2, \dots, n$. In this study the weights using RE method are calculated, assuming that $p = 2$. In RE method, the data collected from the respondents were analyzed and divided into three groups namely: administrative (G1-RE), academic staff (G2-RE), and postgraduate students (G3-RE). The

normalized weights of all groups are presented as Final Weights for RE method (FW-RE) (see Table 6.3).

Table 6.3

The Weights and Rank for the Criteria Using RE Method

Groups	C_1 (Rank)	C_2 (Rank)	C_3 (Rank)	C_4 (Rank)	C_5 (Rank)
G1-RE	0.2520(2)	0.0917(4)	0.0888(5)	0.3786(1)	0.1888(3)
G2-RE	0.3036(1)	0.1875(3)	0.1399(5)	0.2058(2)	0.1633(4)
G3-RE	0.3610(1)	0.0798(4)	0.0548(5)	0.3583(2)	0.1461(3)
G. Mean	0.3023	0.1111	0.0880	0.3034	0.1652
FW-RE	0.3116(2)	0.1145(4)	0.0907(5)	0.3128(1)	0.1703(3)

The analysis in RE method indicated that the group 1 evaluated C_4 to be the most important, as well as group 2 and 3 evaluated C_1 to be preferred than others. Through the results in Table 6.3, it can be seen the final weights by using G. Mean for all groups in RE method (FW-RE) has shown that the C_4 is the most important than others. Similarly, the analyses by using this method is presented in Figure 5.3.

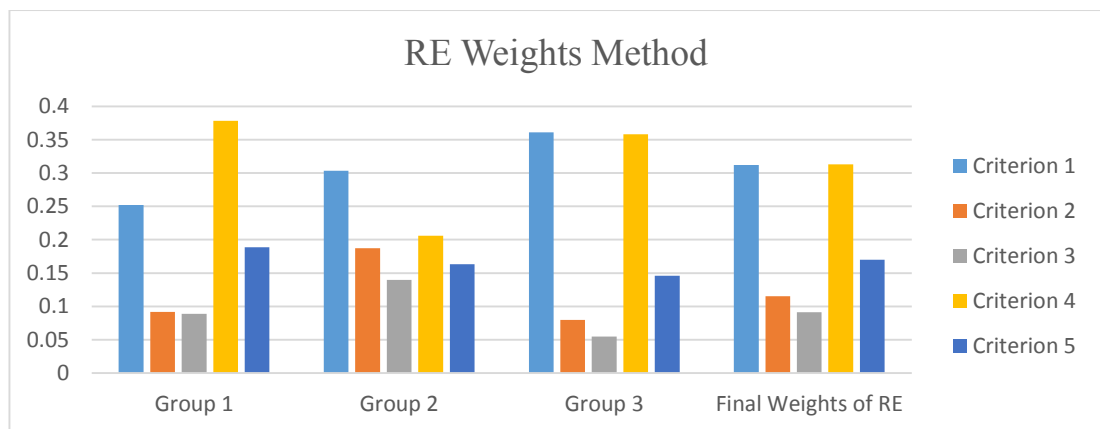


Figure 6.3. The criteria weights using RE method

6.2.4 ROC Method

The same processes as stated in previous methods were carried out, but the criteria weights were calculated by using ROC method. In this technique, the data collected from the respondents were analyzed and divided into three groups namely: administrative (G1-ROC), academic staff (G2-ROC), and postgraduate students (G3-ROC). Normalized weights of criteria were computed using Equation (6.4). The normalized weights of all groups are denoted as Final Weights for ROC method (FW-ROC) as shown in Table 6.4.

$$w_i(ROC) = \frac{1}{K} \sum_{r=1}^K \frac{1}{r} \quad (6.4)$$

Where K is the number of criteria, r is the rank position of criterion i , $i = 1, 2, \dots, K$.

Table 6.4

The Weights and Rank for the Criteria Using ROC Method

Groups	C_1 (Rank)	C_2 (Rank)	C_3 (Rank)	C_4 (Rank)	C_5 (Rank)
G1-ROC	0.2379(2)	0.1129(5)	0.1144(4)	0.3325(1)	0.2023(3)
G2-ROC	0.2684(1)	0.1855(3)	0.1612(5)	0.2038(2)	0.1810(4)
G3-ROC	0.3268(2)	0.1018(4)	0.0805(5)	0.3327(1)	0.1582(3)
G. Mean	0.2753	0.1287	0.1141	0.2825	0.1796
FW-ROC	0.2809(2)	0.1313(4)	0.1164(5)	0.2882(1)	0.1832(3)

Based on the results in Table 6.4, it can be observed that the group 1 and 3 were estimated C_4 to be chosen as the most important than others, whereas group 2 preferred C_1 as the most important criterion than others. The final weights based on G. Mean in ROC method (FW-ROC) presented that the C_4 is the preferred criterion

than others. Correspondingly, the criteria weights using this method is shown in Figure 6.4.

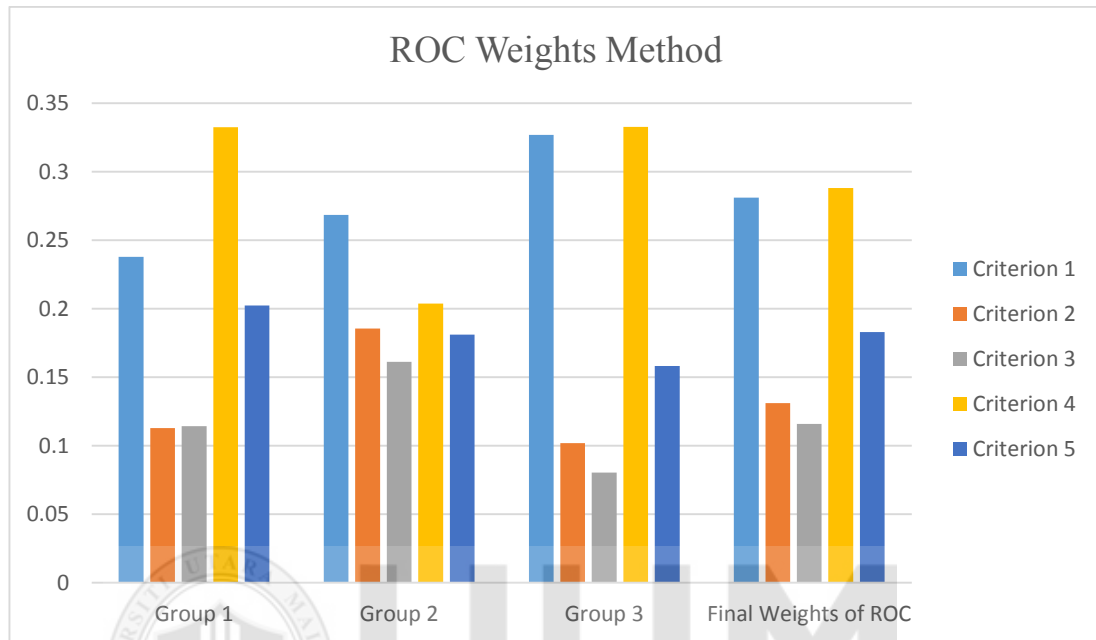


Figure 6.4. The criteria weights using ROC method

6.2.5 RM Method

Similar processes were repeated as previously mentioned, but now criteria weights were calculated by using RM technique. In the RM procedure, the value for each criterion is divided with the least important criterion. Let w_j be a weight for criterion j , $j = 1, \dots, n$. Let w^* be the weight for the least important criterion. So the raw weight for criterion j is w_j/w^* , and then normalizing the weights. In RM method, the respondents data were analyzed and divided into three groups namely: administrative (G1-RM), academic staff (G2-RM), and postgraduate students (G3-RM). The normalized weights of all groups are represented as Final Weights for RM method (FW-RM) as presented in Table 6.5.

Table 6.5

The Weights and Rank for the Criteria Using RM Method

Groups	C_1 (Rank)	C_2 (Rank)	C_3 (Rank)	C_4 (Rank)	C_5 (Rank)
G1-RM	0.2220(2)	0.1496(4)	0.1490(5)	0.2646(1)	0.2148(3)
G2-RM	0.2283(1)	0.1896(4)	0.1787(5)	0.2084(2)	0.1950(3)
G3-RM	0.2598(2)	0.1476(4)	0.1346(5)	0.2640(1)	0.1941(3)
G. Mean	0.2361	0.1612	0.1530	0.2442	0.2011
FW-RM	0.2371(2)	0.1619(4)	0.1537(5)	0.2453(1)	0.2020(3)

The evaluations in Table 6.5 displayed that the group 1 and 3 has assessed C_4 to be the most preferred than others, although group 2 preferred C_1 than others. In RM method, the final weights by using G. Mean for all groups (FW-RM) revealed that the C_4 is the most important than others. Moreover, the analysis by using RM method is shown in Figure 6.5.

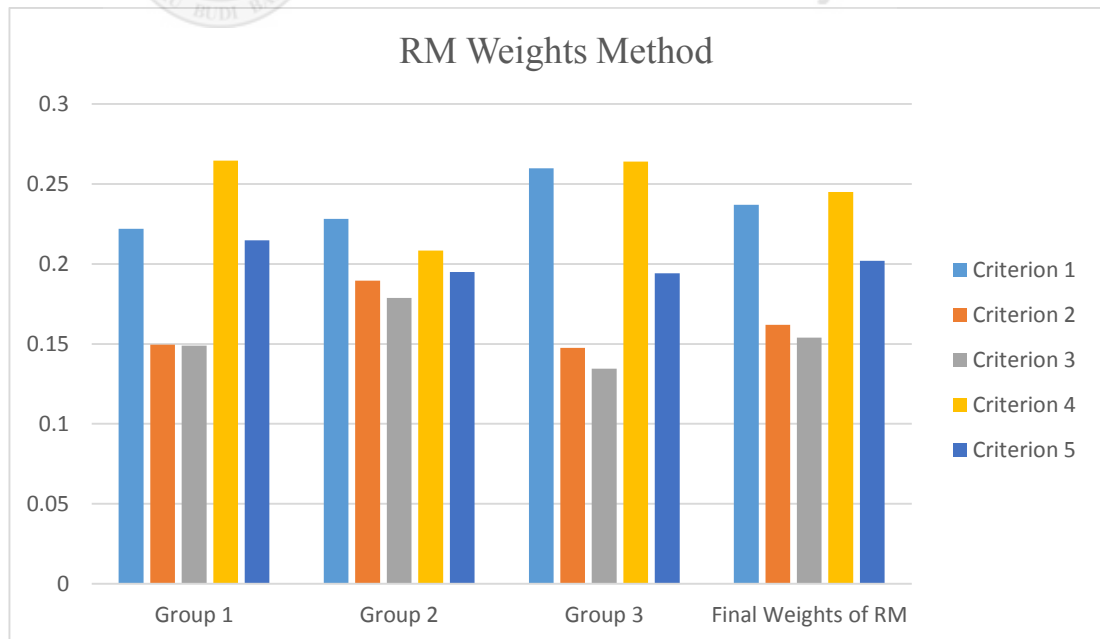


Figure 6.5. The criteria weights using RM method

6.2.6 RW Method

The RW technique requires the DM to first rank the related attributes according to their importance. The least important attribute is allocated in a weight of ten, and all others are judged as multiples of ten. The weight of a criterion is obtained by dividing the criterion's weight with the sum of all attributes' weights. In RW method, the respondents' data were analyzed and divided into three groups namely: administrative (G1-RW), academic staff (G2-RW), and postgraduate students (G3-RW). Criteria weights by using RW method have been computed for each group as well as the normalized weights of all group. The normalized weights of all groups are presented as Final Weights for RW method (FW-RW) as displayed in Table 6.6.

Table 6.6

The Weights and Rank for the Criteria Using RW Method

Groups	C_1 (Rank)	C_2 (Rank)	C_3 (Rank)	C_4 (Rank)	C_5 (Rank)
G1-RW	0.2478(2)	0.1285(4)	0.1130(5)	0.3134(1)	0.1973(3)
G2-RW	0.2775(1)	0.2014(3)	0.1516(5)	0.2027(2)	0.1668(4)
G3-RW	0.3089(2)	0.1164(4)	0.0887(5)	0.3111(1)	0.1748(3)
G. Mean	0.2769	0.1444	0.1150	0.2704	0.1792
FW-RW	0.2809(1)	0.1465(4)	0.1166(5)	0.2743(2)	0.1818(3)

The results in Table 6.6 by using RW method presented C_1 as the most important than others with group 2. At the same context, the C_4 was preferred from group 1 and 3 more than others. The final weights for all groups in RW method (FW-RW) indicated that the C_1 is the most important than others. Furthermore, the evaluation by using this method is displayed in Figure 6.6.

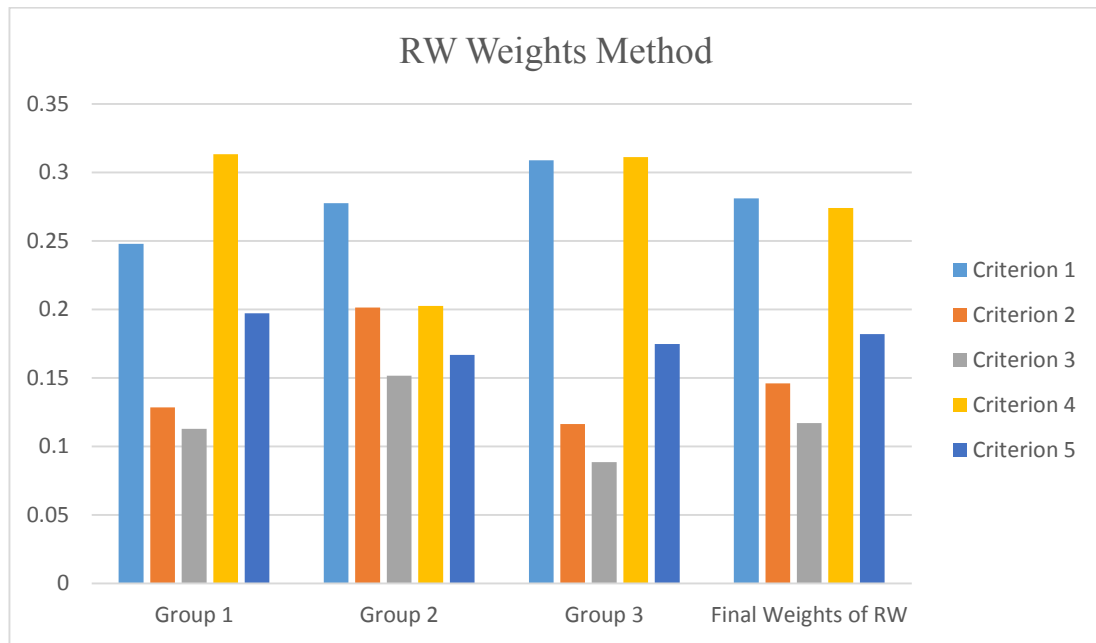


Figure 6.6. The criteria weights using RW method

6.2.7 DPA Method

In DPA weighting process, the DM has a 'budget' of points to assign the attributes directly to reflect their relative importance. The total of all attribute weights must be sum up to 100. Clearly, in DPA there is no need to normalize the weights since the sum of 100 is already prescribed. In DPA technique, the data collected from the respondents were analyzed and divided into three groups namely: administrative (G1-DPA), academic staff (G2-DPA), and postgraduate students (G3-DPA). Normalized weights by using DPA method have been calculated for each group as well as the normalized weights of all group as shown in Table 6.7. The normalized weights of all groups are represented as Final Weights for DPA method (FW-DPA).

Table 6.7

The Weights and Rank for the Criteria Using DPA Method

Groups	C_1 (Rank)	C_2 (Rank)	C_3 (Rank)	C_4 (Rank)	C_5 (Rank)
G1-DPA	0.2371(2)	0.1415(4)	0.1336(5)	0.2897(1)	0.1981(3)
G2-DPA	0.2722(1)	0.1865(3)	0.1542(5)	0.2089(2)	0.1782(4)
G3-DPA	0.3104(1)	0.1252(4)	0.0990(5)	0.2973(2)	0.1681(3)
G. Mean	0.2716	0.1489	0.1268	0.2620	0.1810
FW-DPA	0.2743(1)	0.1504(4)	0.1280(5)	0.2646(2)	0.1828(3)

The DPA method produced values for criteria weights with regard to each group as shown in Table 6.7. It can be observed that the group 2 and 3 estimated C_1 to be most preferred than others, whereas group 1 preferred C_4 as the most important criterion than others. The final weights for all groups in DPA method (FW- DPA) displayed that the C_1 is the most important than others. Besides, the analysis by using this method are displayed in Figure 6.7.

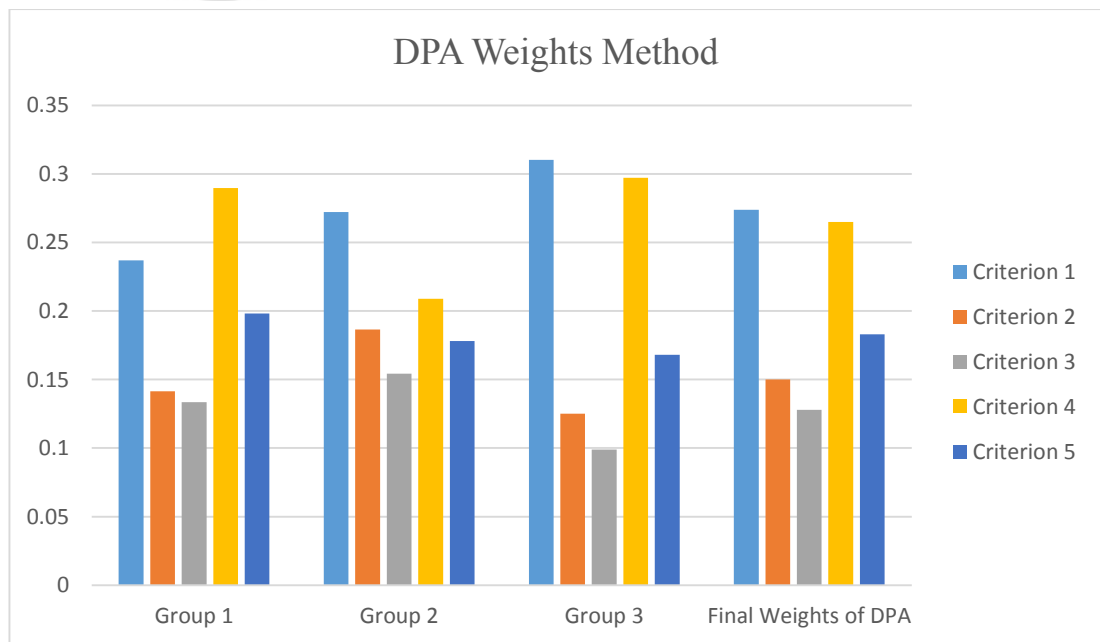


Figure 6.7. The criteria weights using DPA method

6.2.8 GW Method

The GW technique is applied to allocate criteria weights by requiring a DM to place a mark on a horizontal line. That means, the criterion is either more, equally or less important than another criterion by a factor of 1 – 9, and then build the decision matrix as in pairwise comparisons (PCs). Therefore, a quantitative weight for a criterion can be calculated by taking the sum of each row and then normalized scores to obtain an overall weights vectors. In GW method, the collected data from the respondents were analyzed and divided into three groups namely: administrative (G1-GW), academic staff (G2-GW), and postgraduate students (G3-GW). The normalized weights of each group and all group were computed by using GW method. The normalized weights of all groups are denoted as Final Weights for GW method (FW-GW) as displayed in Table 6.8.

Table 6.8

The Weights and Rank for the Criteria Using GW Method

Groups	C_1 (Rank)	C_2 (Rank)	C_3 (Rank)	C_4 (Rank)	C_5 (Rank)
G1-GW	0.2332(2)	0.1297(5)	0.1534(4)	0.2917(1)	0.1919(3)
G2-GW	0.2381(1)	0.2010(3)	0.1773(5)	0.2031(2)	0.1805(4)
G3-GW	0.3140(2)	0.1041(4)	0.0848(5)	0.3339(1)	0.1633(3)
G. Mean	0.2593	0.1395	0.1321	0.2705	0.1782
FW-GW	0.2647(2)	0.1424(5)	0.1349(4)	0.2761(1)	0.1819(3)

Through the results in Table 6.8, it can be seen that the group 2 preferred C_1 than others, while group 1 and 3 preferred C_4 to be the most important than others. The final weights by using G. Mean for all groups in GW method (FW-GW) has shown

that the C_4 is the most important than others. Also, the results by using this method is displayed in Figure 6.8.

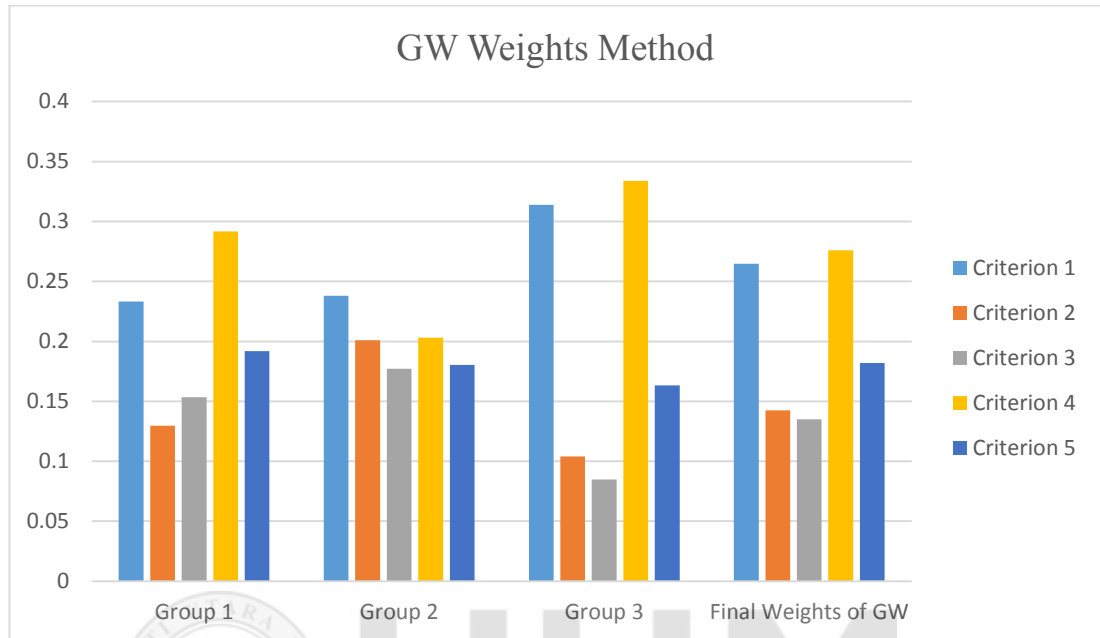


Figure 6.8. The criteria weights using GW method

6.2.9 PCs Method

The pairwise judgments in this technique are structured in a PC matrix, and a prioritization procedure is implemented to draw a corresponding priority vector. PCs is an important phase in AHP to be completed by the experts. However, AHP is widely criticized for being such a tedious process, especially with inconsistency judgments. This study has some inconsistency judgments as illustrated in the following subsections.

6.2.9.1 Inconsistency Indicators

In this study, 12 out of 95 judgments in PC matrix were inconsistent (refer Appendix E), six of them were from the administrative group (G1), five of them were from the academic staff group (G2), and only one was from postgraduate students group (G3).

Appendix E displays inconsistent PC matrix in the first part, then displays the corrected matrices in the second part for all groups. For example, the following Figure 6.9 displays the inconsistency matrix and corrected matrix by TROI method with regard respondent number 14 in G1, with indicating to Consistency Ratio (CR).

1	0.33	0.25	0.5	2		1	0.33	0.25	0.5	2
3	1	0.33	3	0.2		3	1	0.5	2	5
4	3	1	0.33	0.14	TROI	4	2	1	3	6
2	0.33	3	1	0.25		2	0.5	0.33	1	4
0.5	5	7	4	1		0.5	0.2	0.17	0.25	1
Matrix A CR= 0.58						Matrix B CR=0.014				

Figure 6.9. Inconsistency matrix and corrected matrix

Based on Figure 6.9, the matrix A has inconsistent judgments with CR=0.58. This matrix has been addressed by proposed TROI method (Appendix H) to be consistent, and the new corrected judgments is presented in matrix B with CR=0.014.

Table 6.9 displays the number of participants in each group as in column 2, with the weights based on their judgments in columns 3-7, as well as the consistency ratios (CR) in the last column has shown that all the ratios were inconsistent with more than 10% for all the groups.

Table 6.9

Inconsistency Indicators of All Groups

No.	participants	C_1	C_2	C_3	C_4	C_5	CR
<i>G1</i>							
1	P3	0.119	0.056	0.262	0.509	0.054	16.7%
2	P5	0.125	0.044	0.053	0.459	0.318	10.3%
3	P7	0.087	0.201	0.049	0.442	0.221	11.1%
4	P14	0.143	0.151	0.171	0.143	0.392	58.1%
5	P17	0.158	0.068	0.14	0.357	0.277	61%
6	P18	0.31	0.212	0.232	0.195	0.051	51%
<i>G2</i>							
7	P4	0.155	0.094	0.142	0.438	0.171	42.3%
8	P7	0.105	0.431	0.275	0.088	0.102	15%
9	P15	0.427	0.148	0.054	0.187	0.184	27.3%
10	P24	0.184	0.079	0.039	0.38	0.318	27.4%
11	P27	0.316	0.081	0.039	0.292	0.271	18%
<i>G3</i>							
12	P5	0.108	0.065	0.039	0.472	0.315	12.3%

Based on Table 6.9, six of evaluators or participants had given inconsistent judgments in group 1. In group 2, five of matrices were inconsistent which given by five of participants, while the only matrix in group 3 was inconsistent which given by participant 5 (P5).

6.2.9.2 The Processing of Inconsistency Matrices by TROI Method

As mentioned in the previous chapter, TROI method was proposed in this study to solve inconsistency problems in PCs without the need to revise from the evaluators. In this study, twelve of PC matrix from the participants in PCs were inconsistent. Therefore, based on TROI method, the inconsistency indicators for all the groups have been addressed as explained in Chapter Four by the illustrative example regarding TROI method. Table 6.10 shows the final weights for all the groups dealt

by TROI method by MATLAB program (see Appendix H), with the new consistency ratios at the last column.

Table 6.10

The Final Weights Using TROI Method

No.	participants	C_1	C_2	C_3	C_4	C_5	CR
<i>G1</i>							
1	P3	0.123	0.072	0.303	0.455	0.047	1.7%
2	P5	0.121	0.037	0.054	0.268	0.521	3.6%
3	P7	0.084	0.230	0.047	0.493	0.145	2.2%
4	P14	0.094	0.267	0.422	0.165	0.052	1.4%
5	P17	0.135	0.059	0.040	0.459	0.308	2.5%
6	P18	0.218	0.085	0.041	0.523	0.133	2.9%
<i>G2</i>							
7	P4	0.151	0.084	0.278	0.433	0.054	1.2%
8	P7	0.105	0.324	0.190	0.057	0.324	6%
9	P15	0.428	0.041	0.081	0.275	0.176	3%
10	P24	0.135	0.057	0.072	0.630	0.105	5.9%
11	P27	0.281	0.080	0.040	0.477	0.123	3%
<i>G2</i>							
12	P5	0.100	0.054	0.046	0.400	0.400	3.3%

Through Table 6.10 it can be seen that the twelve inconsistent matrices of three groups have been addressed by TROI method. For instance, in the administrative group (G1) there are six matrices of inconsistent judgments received from the participants (P3, P5, P7, P14, P17, P18) through the evaluation process on e-learning implementation criteria. After that, these inconsistent matrices were fixed by TROI method to become consistent as the results are shown in Table 6.10.

6.2.9.3 The Weights of PCs Method

In PCs method, the data collected from the respondents were analyzed and divided into three groups administrative (G1-PCs), academic staff (G2-PCs), and postgraduate students (G3-PCs). After processed inconsistent judgments using TROI method, criteria weights of PCs method have been computed for each group as well as the normalized weights for all the groups as presented in Table 6.11. The normalized weights of all groups are shown as Final Weights for PCs method (FW-PCs).

Table 6.11

The Weights for the Criteria Using PCs Method

Groups	C_1 (Rank)	C_2 (Rank)	C_3 (Rank)	C_4 (Rank)	C_5 (Rank)
G1-PCs	0.2294(2)	0.1187(5)	0.1375(4)	0.3305(1)	0.1839(3)
G2-PCs	0.2418(1)	0.1893(3)	0.1852(4)	0.2070(2)	0.1767(5)
G3-PCs	0.3127(2)	0.0993(4)	0.0838(5)	0.3407(1)	0.1635(3)
G. Mean	0.2589	0.1307	0.1287	0.2857	0.1745
FW-PCs	0.2646(2)	0.1336(4)	0.1315(5)	0.2920(1)	0.1783(3)

After addressing the inconsistency judgments as displayed in Table 6.11 through TROI method, the criteria weights were calculated by using PCs method based on the evaluation from 95 participants as shown in Table 6.11. It can be seen that the group 1 and 3 had evaluated C_4 to be most important than others, while group 2 preferred C_1 as the most important criteria as compared to others. The final weights for all groups in PCs method (FW-PCs) presented that the C_4 is the most important than others. Likewise, the weights of criteria by using this method is displayed in Figure 6.10.

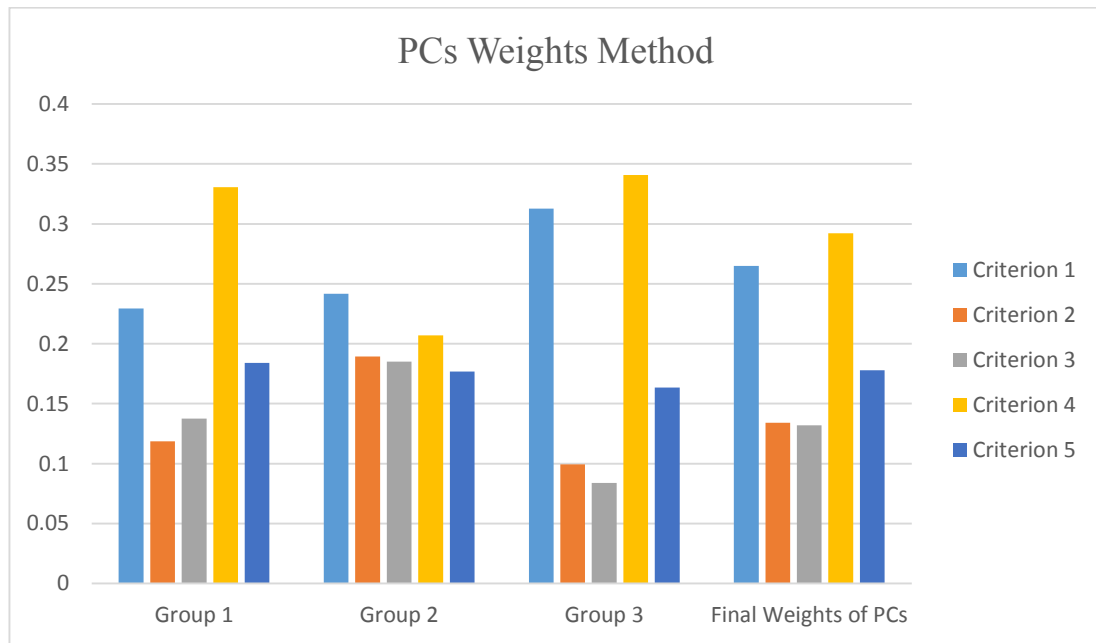


Figure 6.10. The criteria weights using PCs method

6.3 Evaluation of Criteria

The rankings from the 95 evaluators on e-learning criteria have been collected and divided into three groups (G1, G2, and G3) as mentioned previously. The data from each group were analyzed by using nine different subjective weights methods (ROC, RE, RR, RS, RM, RW, DPA, GW, and PCs). The next subsections illustrate the evaluation of e-learning criteria based on each group.

6.3.1 Evaluation by the Administrative Group (G1)

Based on the data collected from G1 (22 participants) of each criterion given by each evaluator, criteria weights have been calculated by using ROC, RE, RR, RS, RM, RW, DPA, GW, and PCs methods. The normalized weights by using each method for each criterion are summarized in Table 6.12. After that, the G. Mean was used to obtain the geometric weights for each criterion. Then the weights were normalized

once again to make sure that the sum of weights is one. The normalized weights for G1 are declared as the Final Weights of G1 (FWG1).

Table 6.12

Criteria Weights of G1

Methods	C_1(Rank)	C_2(Rank)	C_3(Rank)	C_4(Rank)	C_5(Rank)
G1-RS	0.2332(2)	0.1407(4)	0.1384(5)	0.2858(1)	0.2018(3)
G1-RR	0.2197(2)	0.1376(5)	0.1459(4)	0.2841(1)	0.2127(3)
G1-RE	0.2520(2)	0.0917(4)	0.0888(5)	0.3786(1)	0.1888(3)
G1-ROC	0.2379(2)	0.1129(5)	0.1144(4)	0.3325(1)	0.2023(3)
G1-RM	0.2220(2)	0.1496(4)	0.1490(5)	0.2646(1)	0.2148(3)
G1-RW	0.2478(2)	0.1285(4)	0.1130(5)	0.3134(1)	0.1973(3)
G1-DPA	0.2371(2)	0.1415(4)	0.1336(5)	0.2897(1)	0.1981(3)
G1-GW	0.2332(2)	0.1297(5)	0.1534(4)	0.2917(1)	0.1919(3)
G1-PCs	0.2294(2)	0.1187(5)	0.1375(4)	0.3305(1)	0.1839(3)
G. Mean	0.2345	0.1267	0.1288	0.3062	0.1988
FWG1	0.2357(2)	0.1273(5)	0.1294(4)	0.3078(1)	0.1998(3)

Based on the final normalized weights of G1 in Table 6.12, it can be observed that the C_4 declared as the most important criteria. In G1, nine of different subjective weights methods have been given the same ranking with regard to C_1 , C_4 , and C_5 . While, these methods produced different ranking with regard to C_2 and C_3 . Similarly the criteria weights using nine subjective methods as well as the final weights for G1 is displayed in Figure 6.11.

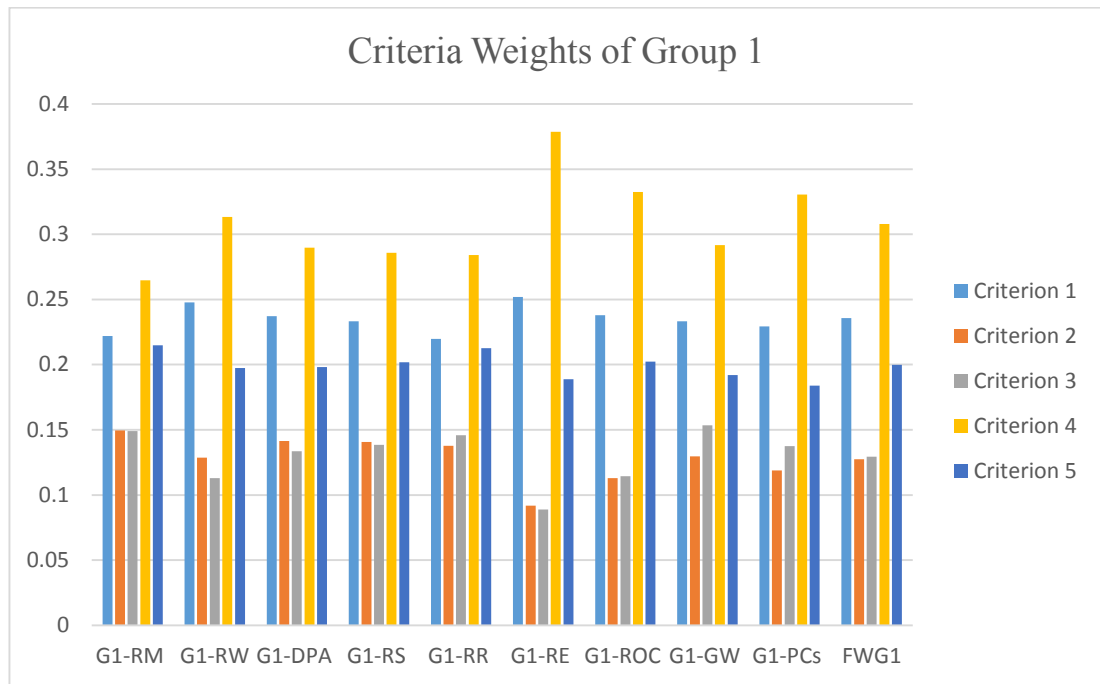


Figure 6.11. Criteria weights of G1

6.3.1.1 Decision of the Optimal Weights by G1

Now, in order to determine the most accurate weights or the optimal weights among the nine subjective weights methods for each group, the proposed decision framework was applied where the absolute difference had been used to make comparisons among criteria weights that were obtained from the weights methods.

The absolute difference between each criterion weight in G1 for each method with the Final Weight (FWG1) for the same respective criterion was calculated. After that, the sum of all absolute differences for each weighting method was calculated as summarized in column 8 as in Table 6.13. The method that has the smallest sum of absolute difference would be declared as the most accurate or the optimal weights.

Table 6.13

Comparison Weights Methods by G1

No.	Difference	C_1	C_2	C_3	C_4	C_5	Sum	Rank
1	G1_RS – FWG1	0.0025	0.0134	0.0090	0.0220	0.0020	0.0489	3
2	G1_RR – FWG1	0.0160	0.0103	0.0165	0.0237	0.0129	0.0794	7
3	G1_RE – FWG1	0.0163	0.0356	0.0406	0.0708	0.0110	0.1743	9
4	G1_ROC – FWG1	0.0022	0.0144	0.0150	0.0247	0.0025	0.0588	5
5	G1_RM – FWG1	0.0137	0.0223	0.0196	0.0432	0.0150	0.1138	8
6	G1_RW – FWG1	0.0121	0.0012	0.0164	0.0056	0.0025	0.0378	1
7	G1_DPA – FWG1	0.0014	0.0142	0.0042	0.0181	0.0017	0.0396	2
8	G1_GW – FWG1	0.0025	0.0024	0.0240	0.0161	0.0079	0.0529	4
9	G1_PCs – FWG1	0.0063	0.0086	0.0081	0.0227	0.0159	0.0616	6

Based on Table 6.13 it can be observed that the absolute differences in each normalized weights from each method with the normalized weights in G1 (FWG1) have been compared for all criteria. The sum of the results was calculated and the smallest sum of absolute difference would be declared as the most accurate way. In G1, the most accurate method which has the smallest value with 0.0378 in column 8 in Table 6.13 is RW method. The RW method declared as the best weights method in G1.

6.3.2 Evaluation by the Academic Staff Group (G2)

Based on the data gathered from G2 (38 participants) of each criterion provided by each evaluator, criteria weights were determined by utilizing ROC, RE, RR, RS, RM, RW, DPA, GW, and PCs methods. The normalized weights from each technique for every criterion are summed up in Table 6.14. After that, the G. Mean was used to obtain the geometric weights for each criterion. Then the weights were normalized

once again to make sure that the sum of weights is one. The normalized weights are stated as the Final Weights of G2 (FWG2).

Table 6.14

Criteria Weights by G2

Methods	$C_1(\text{Rank})$	$C_2(\text{Rank})$	$C_3(\text{Rank})$	$C_4(\text{Rank})$	$C_5(\text{Rank})$
G2-RS	0.2487(1)	0.1954(3)	0.1688(5)	0.2047(2)	0.1824(4)
G2-RR	0.2340(1)	0.1822(5)	0.1848(4)	0.1999(2)	0.1991(3)
G2-RE	0.3036(1)	0.1875(3)	0.1399(5)	0.2058(2)	0.1633(4)
G2-ROC	0.2684(1)	0.1855(3)	0.1612(5)	0.2038(2)	0.1810(4)
G2-RM	0.2283(1)	0.1896(4)	0.1787(5)	0.2084(2)	0.1950(3)
G2-RW	0.2775(1)	0.2014(3)	0.1516(5)	0.2027(2)	0.1668(4)
G2-DPA	0.2722(1)	0.1865(3)	0.1542(5)	0.2089(2)	0.1782(4)
G2-GW	0.2381(1)	0.2010(3)	0.1773(5)	0.2031(2)	0.1805(4)
G2-PCs	0.2418(1)	0.1893(3)	0.1852(4)	0.2070(2)	0.1767(5)
G. mean	0.2560	0.1908	0.1662	0.2049	0.1800
FWG2	0.2565(1)	0.1912(3)	0.1665(1)	0.2053(2)	0.1804(4)

Through the analysis using nine different subjective methods as well as FWG2, the results in Table 6.14 has shown that the G2 presented the C_1 as the most important than others. On the another hand, In G2, nine of weights methods gave the same ranking regarding C_1 , and C_4 . Whereas, these methods had produced different ranking with regard to C_2 , C_3 , and C_5 . For further clarification, the criteria weights and FW for G2 is displayed in Figure 6.12.

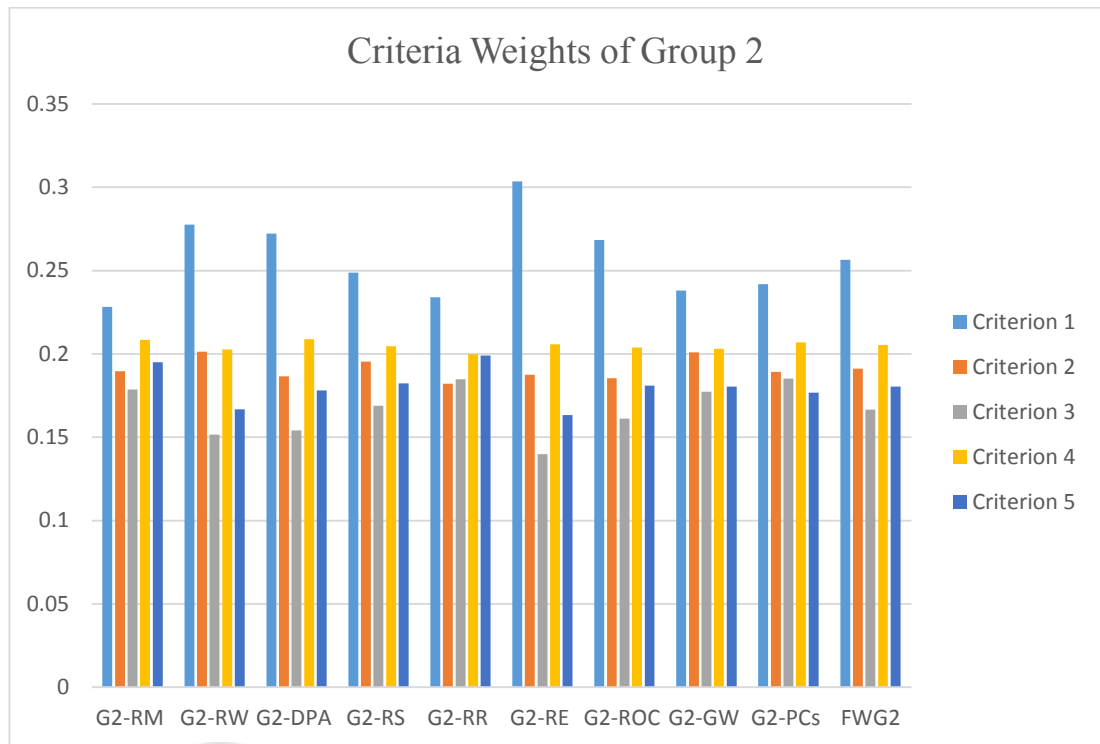


Figure 6.12. Criteria weights of G2

6.3.2.1 Decision of the Optimal Weights by G2

A similar process with the comparisons in G1, the absolute difference in G2 between each criterion weight for every technique with the Final Weight for G2 (FWG2) has been computed. The method that has the smallest sum of absolute difference would be declared as the optimal method as displayed in Table 6.15.

Table 6.15

Comparison Weights Methods by G2

No	Difference	C_1	C_2	C_3	C_4	C_5	Sum	Rank
1	G2_RS – FWG2	0.0078	0.0042	0.0023	0.0006	0.0020	0.0169	1
2	G2_RR – FWG2	0.0225	0.0090	0.0183	0.0054	0.0187	0.0739	8
3	G2_RE – FWG2	0.0471	0.0037	0.0266	0.0005	0.0171	0.0950	9
4	G2_ROC – FWG2	0.0119	0.0057	0.0053	0.0015	0.0006	0.0250	2
5	G2_RM – FWG2	0.0282	0.0016	0.0122	0.0031	0.0146	0.0597	6
6	G2_RW – FWG2	0.0210	0.0102	0.0149	0.0026	0.0136	0.0623	7
7	G2_DPA – FWG2	0.0157	0.0047	0.0123	0.0036	0.0022	0.0385	3
8	G2_GW – FWG2	0.0184	0.0098	0.0108	0.0022	0.0001	0.0413	5
9	G2_PCs – FWG2	0.0147	0.0019	0.0187	0.0017	0.0037	0.0407	4

Through the Table 6.15, it can be seen that the smallest sum of the absolute difference in G2 is 0.0169 with the RS method, and this method would be declared as the most accurate or optimal method in G2.

6.3.3 Evaluation by the Postgraduate Students Group (G3)

The data collected from G3 (35 participants) of each criterion supplied by each evaluator, criteria weights have been identified by using ROC, RE, RR, RS, RM, RW, DPA, GW, and PCs methods. The normalized weights from each approach for every criterion are displayed in Table 6.16. The G. Mean has been used to get the geometric weights for each criterion. At that time, the weights have been normalized once again for each criterion. The normalized weights are mentioned as the Final Weights of G3 (FWG3).

Table 6.16

Criteria weights of G3

Methods	C_1 (Rank)	C_2 (Rank)	C_3 (Rank)	C_4 (Rank)	C_5 (Rank)
G3-RS	0.2863(1)	0.1347(4)	0.1116(5)	0.2853(2)	0.1821(3)
G3-RR	0.2867(2)	0.1282(4)	0.1175(5)	0.2994(1)	0.1682(3)
G3-RE	0.3610(1)	0.0798(4)	0.0548(5)	0.3583(2)	0.1461(3)
G3-ROC	0.3268(2)	0.1018(4)	0.0805(5)	0.3327(1)	0.1582(3)
G3-RM	0.2598(2)	0.1476(4)	0.1346(5)	0.2640(1)	0.1941(3)
G3-RW	0.3089(2)	0.1164(4)	0.0887(5)	0.3111(1)	0.1748(3)
G3-DPA	0.3104(1)	0.1252(4)	0.0990(5)	0.2973(2)	0.1681(3)
G3-GW	0.3140(2)	0.1041(4)	0.0848(5)	0.3339(1)	0.1633(3)
G3-PCs	0.3127(2)	0.0993(4)	0.0838(5)	0.3407(1)	0.1635(3)
G. mean	0.3062	0.1135	0.0923	0.3123	0.1682
FWG3	0.3085(2)	0.1144(4)	0.0930(5)	0.3147(1)	0.1695(3)

Based on Table 6.16, nine of weights methods has given different ranking with regard to C_1 , and C_4 . In this group, the C_1 was preferred by using DPA, RS, and RE. While, the C_4 was preferred by using the rest of methods. Besides, these methods had produced the same ranking with regard to C_2 , C_3 , and C_5 . Based on the final normalized weights of G3, it can be observed that the C_4 is declared as the most important than others. Similarly, the criteria weights using nine methods and also the FW for G3 are displayed in Figure 6.13.

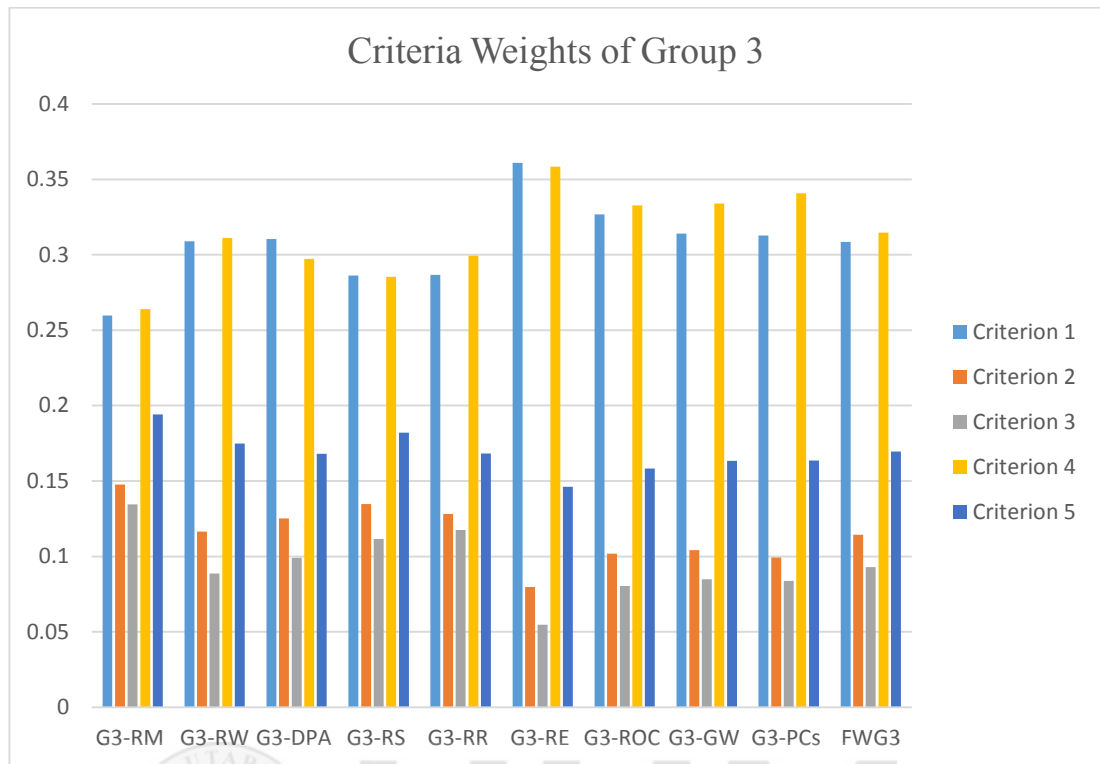


Figure 6.13. Criteria weights of G3

6.3.3.1 Decision of the Optimal Weights by G3

The absolute difference in G3 between each criterion weight of each method with the Final Weight (FWG3) was calculated. The smallest sum of absolute difference denoted as the most accurate weights as showed in Table 6.17.

Table 6.17

Comparison Weights Methods of G3

No.	Difference	C_1	C_2	C_3	C_4	C_5	Sum	Rank
1	G3_RS – FWG3	0.0222	0.0203	0.0186	0.0294	0.0126	0.1031	7
2	G3_RR – FWG3	0.0218	0.0138	0.0245	0.0153	0.0013	0.0767	6
3	G3_RE – FWG3	0.0525	0.0346	0.0382	0.0436	0.0234	0.1923	8
4	G3_ROC – FWG3	0.0183	0.0126	0.0125	0.0180	0.0113	0.0727	5
5	G3_RM – FWG3	0.0487	0.0332	0.0416	0.0507	0.0246	0.1988	9
6	G3_RW – FWG3	0.0004	0.0020	0.0043	0.0036	0.0053	0.0156	1
7	G3_DPA – FWG3	0.0019	0.0108	0.0060	0.0174	0.0014	0.0375	2
8	G3_GW – FWG3	0.0055	0.0103	0.0082	0.0192	0.0062	0.0494	3
9	G3_PC _s – FWG3	0.0042	0.0151	0.0092	0.0260	0.0060	0.0605	4

The result in Table 6.17 has shown that the smallest sum of absolute difference is 0.0156 with the RW method, which means that the weights under this RW method is the most accurate in this group.

6.3.4 Evaluation by All Groups

Based on the normalized weights of each criterion given by each group (FWG1, FWG2, and FWG3), criteria weights have been calculated by using G. Mean to get the geometric weights for each criterion. Then the weights were normalized once again to get the final weights for all groups. The normalized weights are declared as the Ideal Weights for all groups from all methods (IW). The summary of the geometric weights and their normalized weights are given in Table 6.18.

Table 6.18

Criteria Weights of All Group

Groups	$C_1(\text{Rank})$	$C_2(\text{Rank})$	$C_3(\text{Rank})$	$C_4(\text{Rank})$	$C_5(\text{Rank})$
FWG1	0.2357(2)	0.1273(5)	0.1294(4)	0.3078(1)	0.1998(3)
FWG2	0.2565(1)	0.1912(3)	0.1665(5)	0.2053(2)	0.1804(4)
FWG3	0.3085(2)	0.1144(4)	0.0930(5)	0.3147(1)	0.1695(3)
G-Mean	0.2652	0.1407	0.1261	0.2709	0.1828
IW	0.2690(2)	0.1428(4)	0.1279(5)	0.2748(1)	0.1855(3)

The Table 6.18 and Figure 6.14 displayed the normalized weights (or FW) for each group (FWG1, FWG2, and FWG3) which have been calculated by using a geometric average based on nine weights methods. Next, each of these weights was used for comparison with total normalized weights in each method. The final normalized weights for all groups obtained from all methods declared as Ideal Weights (IW). The IW have been identified through G. Mean to obtain the average weights, in order to use IW for comparison among the methods.

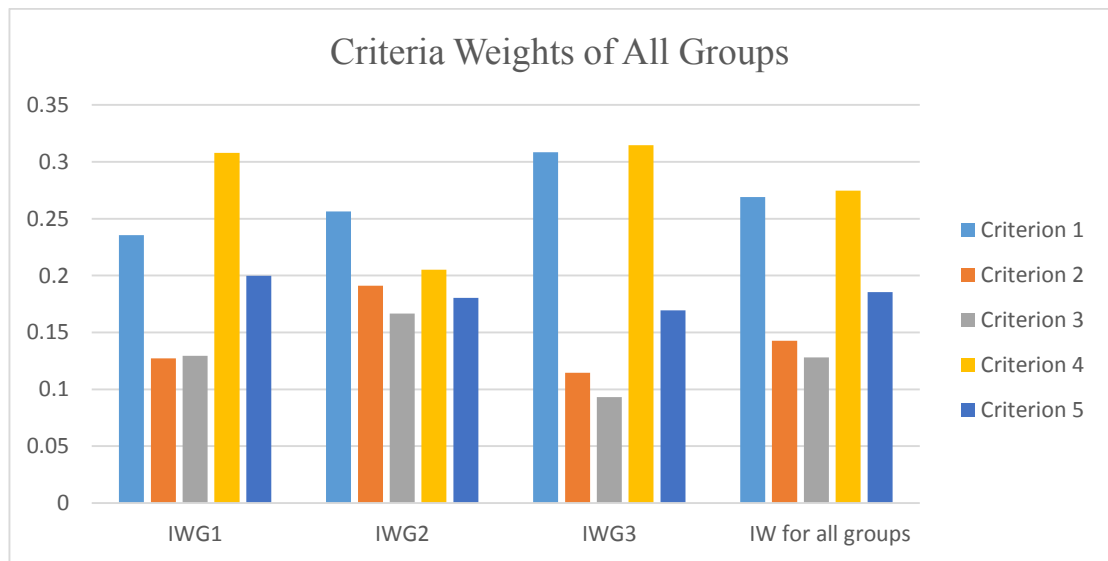


Figure 6.14. Criteria weights of all group

6.3.4.1 Decision of the Optimal Weights by All Groups

Now, in order to know that which method for all groups is the most accurate weights, the absolute difference between each final criterion weight of methods with the total Ideal Weight (IW) for all groups was calculated. After that, the sum of all absolute differences for each weighting method was calculated as summarized in Table 6.19. The method that has the smallest sum of absolute difference is declared as the most accurate or optimal weights method.

Table 6.19

Comparison Weights Methods

No.	Difference	C_1	C_2	C_3	C_4	C_5	Sum	Rank
4	FW_RS – IW	0.0117	0.0132	0.0109	0.0170	0.01901	0.0718	6
5	FW_RR – IW	0.0211	0.0064	0.0206	0.0149	0.0090	0.0720	7
6	FW_RE – IW	0.0426	0.0283	0.0372	0.0380	0.0152	0.1613	9
7	FW_ROC – IW	0.0119	0.0115	0.0115	0.0134	0.0023	0.0506	5
1	FW_RM – IW	0.0319	0.0191	0.0258	0.0295	0.0165	0.1228	8
2	FW_RW – IW	0.0119	0.0037	0.0113	0.0005	0.0037	0.0311	3
3	FW_DPA – IW	0.0053	0.0076	0.0001	0.0102	0.0027	0.0259	2
8	FW_GW – IW	0.0043	0.0004	0.0070	0.0013	0.0036	0.0166	1
9	FW_PCs – IW	0.0044	0.0092	0.0036	0.0172	0.0072	0.0416	4

Table 6.19 displayed the absolute differences for each normalized weights from each method with the IW for all groups. In order to know which weights method is the optimal, the smallest sum of the absolute difference is 0.0166 with GW method, which means that this method is declared as the most accurate weights for all groups or the optimal method of subjective weighting methods.

6.4 Best Ranked Criteria Weights

Based on the comparisons among weights methods, RW method weights have the least sum of absolute differences in G1 with the score of 0.0378. Therefore, the criteria weights in RW method is declared as the most accurate weights or optimal weights in G1. While the optimal method of criteria weights in G2 that has the least sum of absolute differences was RS method with the score of 0.0169. The RW method once again has the least sum of absolute differences in G3 with the score of 0.0156. Consequently, the optimal criteria weights for all groups based on the comparison of the methods is GW method, which has the least sum of absolute differences with the score of 0.0166. Table 6.20 displayed the optimal method from each group, together with the optimal weights method for all groups.

Table 6.20

The Best-Ranked Criteria Weights

Groups	Methods	C_1	C_2	C_3	C_4	C_5
G1	RW	0.2478(2)	0.1285(4)	0.1130(5)	0.3134(1)	0.1973(3)
G2	RS	0.2487(1)	0.1954(3)	0.1688(3)	0.2047(2)	0.1824(4)
G3	RW	0.3089(2)	0.1164(4)	0.0887(5)	0.3111(1)	0.1748(3)
All groups	GW	0.2647(2)	0.1424(5)	0.1349(4)	0.2761(1)	0.1819(3)

Obviously, based on the average weights of a different number of evaluators (22 of G1, 38 of G2, 35 of G3) achieved by using various weighting methods, there is no specific weights method is the best. Logically, the real meaning of criteria weights was obtained by using various weights methods for all groups. This way is necessary for avoiding inaccurate weights of the MCDM methods and obtaining positive

outcomes. In this study, the decision framework is applied on several subjective weighting methods for selecting the optimal method to assign weights for e-learning criteria. The GW method has been found to be the optimal method for all groups in calculating criteria weights on e-learning. This set of weights would be used in evaluating the e-learning approaches by using TOPSIS method as discussed in the following Section. The best-ranked criteria weights obtained from GW method are shown in Table 6.21.

Table 6.21

Final Result for Criteria Weights

No.	Criteria	Weights	Rank
1	Human resources	0.2647	2
2	Specific ICT infrastructure for e-learning	0.1424	4
3	Basic ICT infrastructure for e-learning	0.1349	5
4	Strategic readiness for e-learning implementation	0.2761	1
5	Legal and formal readiness for e-learning implementation	0.1819	3

The survey results have revealed that the ‘Strategic readiness for e-learning implementation’ criterion is the most important criteria for assigning 27% of weights. The second top priority is ‘Human Resources’ criterion and assigned 26% of weights. On the other side, the “Basic ICT infrastructure for e-learning” had placed as the least important criterion for e-learning.

6.5 Evaluation of the Five E-Learning Approaches Using TOPSIS Method

The following decision matrix in Table 6.22 displays the average of the judgments (G. Mean) for each alternative given by 95 participants in three different groups (administrative, academic staff, and postgraduate students) for the five e-learning approaches.

Table 6.22

Decision Matrices Average from Each Group

Criteria Weights	0.2647	0.1424	0.1349	0.2761	0.1819
G1 Average					
Alternatives	C_1	C_2	C_3	C_4	C_5
Blended learning	74	78	74	75	74
ICT & f-to-f learning	65	62	62	60	60
Flipped learning	83	83	80	84	85
Synchronous learning	40	39	42	38	42
Asynchronous learning	29	26	30	24	29
G2 Average					
Alternatives	C_1	C_2	C_3	C_4	C_5
Blended learning	73	77	80	77	72
ICT & f-to-f learning	69	66	71	64	64
Flipped learning	75	76	76	83	78
Synchronous learning	51	53	57	53	52
Asynchronous learning	40	42	46	41	40
G3 Average					
Alternatives	C_1	C_2	C_3	C_4	C_5
Blended learning	74	71	71	75	72
ICT & f-to-f learning	66	63	60	61	59
Flipped learning	83	81	80	82	88
Synchronous learning	43	43	39	44	37
Asynchronous learning	32	30	30	31	26

The result of the ranking of approaches is derived using RC_i^* as in Equation (4.17) are shown in Table 6.23. The alternative at first rank is considered as the best

maximization of expected benefits of e-learning approaches for implementation in the selected public university.

Table 6.23

Results of TOPSIS Technique for Each Group

G1 results					
Alternatives	S_i^*	S_i^-	$S_i^* + S_i^-$	RC_i^+	Rank
Blended learning	4.772	16.576	21.348	0.776	2
ICT & f-to-f learning	10.734	10.623	21.357	0.497	3
Flipped learning	0	21.260	21.260	1	1
Synchronous learning	18.395	2.872	21.267	0.135	4
Asynchronous learning	21.260	0	21.260	0	5
G2 results					
Blended learning	2.226	12.909	15.135	0.853	2
ICT & f-to-f learning	6.401	8.939	15.340	0.583	3
Flipped learning	0.581	14.630	15.211	0.962	1
Synchronous learning	11.461	3.495	14.956	0.234	4
Asynchronous learning	14.808	0	14.808	0	5
G3 results					
Blended learning	5.313	15.218	20.531	0.741	2
ICT & f-to-f learning	10.363	10.122	20.485	0.494	3
Flipped learning	0	20.324	20.324	1	1
Synchronous learning	17.471	2.917	20.388	0.143	4
Asynchronous learning	20.324	0	20.324	0	5

The results based on the TOPSIS technique in Table 6.23 had shown that the flipped classroom approach is preferred from all the groups for implementation in the selected public university, and it will be recommended to the management of the university. The blended learning was the second most important approach based on the survey participants and followed by ICT supported face-to-face learning, synchronous, and asynchronous learning.

6.6 Validation of the Results

The results of ranking of evaluation e-learning criteria as well as the results of ranking of e-learning approaches were validated by the experts through a questionnaire for validation of final results (see Appendix I). Five e-learning criteria and five e-learning approaches were validated by three experts. The director, deputy director and a trainer in University Teaching and Learning Centre (UTLC) of the selected university, who have experience in e-learning, took part in the survey. The primary function of the UTLC serves most directly through offer innovative programming and professional development resources to explore, develop, and share ideas about teaching that foster innovative environments in which all learners can succeed. Also, the UTLC is interested in piloting innovative course approaches such as e-learning with highly motivated students.

The questionnaire was prepared to ask them to give their level of agreement on the results based on a seven point scale, or scale 1 to 7. The score 1 means that the expert strongly disagrees with the results, while the score 7 means that the expert strongly agrees with the results. All experts had given positive responses for both results whether the ranking of the e-learning approaches or the ranking of the evaluation criteria. The first expert agreed with results of criteria (score 5), and also agreed with result of alternatives (score 6). While the second expert gave the same level of agreement with the results with score of 4 on criteria and alternatives. Finally, the third expert strongly agreed with both of results by giving score 7.

6.7 Discussion

In this research, the selection of the optimal weighting method was achieved by applying the proposed decision for evaluating e-learning criteria. The e-learning criteria were analysed by several subjective weighting methods. In particular, RM, ROC, RE, RR, RS, RW, GW, DPA, and PCs methods were the chosen techniques, because the methods were commonly used in the previous studies. The judgements In PCs given by DMs may not always be consistent for various reasons. This study proposes TROI method to address any inconsistency in PCs without returning judgements to DMs for correction. Thus, in order to know how the optimal weights method to be selected, the absolute differences in each normalized weights from each method with the Ideal Weights (IW) for all methods have been calculated. Then, the smallest sum of the absolute difference means that this method is declared as the most accurate or optimal weights method.

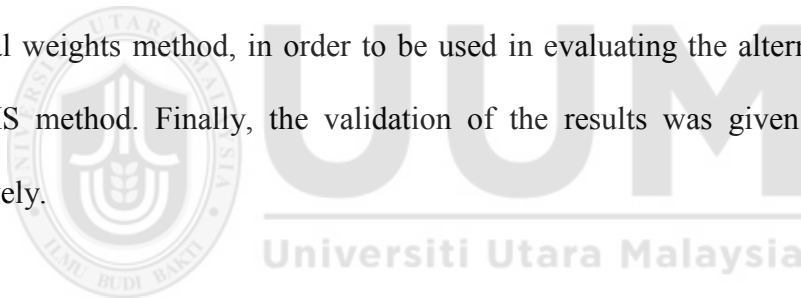
Based on the criteria results, it can be seen that different weighting methods produced different set of weights on the same problem, as well as the weights from different evaluators produced different ranking as well. The proposed decision framework had helped to determine the optimal subjective weighting method. In this study, the GW method has been found to be the optimal weights method for evaluating criteria, and this set of weights were used in evaluating the alternatives by using TOPSIS method. The final results of this study is that the most suitable e-learning approach was the flipped classroom approach, and it is selected by all three groups. The finding in this chapter can be summarized as follows:

- I. The proposed TROI method can be used as a method to rectify the judgments in inconsistent PC matrix. In this chapter twelve inconsistent matrices had been addressed by proposed TROI method. TROI method highlights that not only to address inconsistent indicators in PCs but also can be used to create a new process to PC based on TROI (PC-TROI) for the DM to deals with PCs easily, through reducing comparisons significantly.
- II. The result of the optimal criteria weights for the evaluation of e-learning approaches were obtained when the proposed decision framework were applied. The determination of the optimal subjective weights method was achieved through comparison of different subjective weighting methods with the ideal weights. Here the ideal weights were defined as the geometric means of all weights of all methods. In this study, the optimal criteria weights is GW method.
- III. The ranking of the e-learning approaches obtained by using TOPSIS method was based on the optimal weights of criteria. In this study, the flipped classroom approach is preferred from all the groups in order to be applied in the selected public university.

Based on the literature reviewed, it can be concluded that MCDM emerges to be an appropriate tool to merge and analyse all viewpoints related with the decision-making process, by setting up a relationship between all alternatives and criteria that can affect the decision. In this study, the decision framework had given effective results, and can be extremely successful in any particular application.

6.8 Summary

In this chapter, the evaluation five types of e-learning based on five criteria is presented by implementing the proposed decision framework. Besides, the results would help the management of the selected public university to select a suitable approach of e-learning for the university. First, the data were collected from the selected public university through two sets of a questionnaire. The first set is about the importance of criteria, while the second set concerns about the rating of the performance of each of the e-learning approach under every criterion. The data are then used to analyze criteria weights through proposed decision framework by the comparison among nine different subjective weighting methods for selecting the optimal weights method, in order to be used in evaluating the alternatives by using TOPSIS method. Finally, the validation of the results was given by the experts positively.



CHAPTER SEVEN

CONCLUSION AND RECOMMENDATIONS

This chapter concludes the presentation of this thesis with the following six sections. The first section is the introduction. The second section summarizes the results. The accomplishment of research objectives is in the third section. The fourth section describes the significant contribution of this research. The limitations of the research and some recommendation for future research are prescribed in the fifth and sixth sections.

7.1 Introduction

The judgments given by decision-maker in Pairwise Comparisons (PCs) technique may not always be in a state of consistency (inconsistency problem) for various reasons as described in Section 5.1. Therefore, Tripartite Relations for Overcoming Inconsistency (TROI) method was proposed to formulate an approach for rectifying the inconsistent PC matrix in the AHP method.

The idea of TROI method came out from Rational Choice Theory. This is illustrated in Section 5.2. In fact, there are difficulties encounter some researchers when the judgments are inconsistent, especially when there is a significant number of criteria or alternatives. In inconsistency cases, the researchers need to go back to the evaluator to get new scores or ranks about the criteria. So, it will be a difficult mission for the researchers if the criteria weights are inconsistent. This study addressed this issue by the proposed TROI method without the need a revision from the evaluator. The proposed TROI method is developed based on determining type of

elements, whether integer or fractional in the first row of the PC matrix, and then correction of the rest of judgments are done by some formulas. These are presented in Section 5.5. The improved PC matrix based on the proposed TROI method will always be consistent. Accordingly, Based on the proposed TROI method, a new Pairwise comparisons based on TROI (PC-TROI) is proposed which has the ability to reduce the number of comparisons among criteria, as well as to achieve a consistent pairwise matrix as explained in Section 5.7.

This study focuses on solving MCDM problems especially in selecting the optimal subjective weights method. In the subjective weighting methods, criteria weights are derived from the decision maker's judgment on criteria. This means that the subjective methods are used to determine weights solely according to the preferences of decision makers. Criteria weights determined by the subjective weighting methods reflect the subjective judgment of the decision-maker, but analytical results or rankings of alternatives based on the weights can be influenced by the decision maker due to his/her level of knowledge and experience in the relevant field.

Many different methods have been proposed for assessing criteria weights which are then used to aggregate criterion priority scores. Each weighting method differs in terms of accuracy, ease of use, complexity for users, and theoretical foundations and produces different sets of criteria weights. In addition, different weights methods may yield different ranking for criteria. Thus, the true meaning and the validity of these criteria weights are important through determining the optimal weights for avoiding misuse of the MCDM models.

Based on the literature there is no specific weights method is the best or optimal in subjective weighting methods. Therefore, this study proposed a decision framework to select the optimal weights method for evaluating criteria, through comparison of various subjective weights methods, included PCs method which has inconsistency problem. The optimal weights are necessary for avoiding any inaccurate weights of the MCDM methods and obtaining positive outcomes. This study has successfully developed a decision framework to aid decision makers in choosing the most suitable subjective weighting method for solving multi-criteria problems.

A study is required to evaluate potential e-learning approaches in the selected public university. Every comprehensive university has a three folded goals: teaching, research, and also service to society. In general, academic staff are required to do even more with less, teach more students, supervise more research students, increase more funds for the university, and so forth. Therefore, e-learning system is an effective tool for accomplishing strategic goals of the university as well as it can offer as a stimulant for modification in teaching and learning. Nevertheless, there are several approaches of e-learning for implementation in higher education. As a case study based on the proposed decision framework, this research has solved the problem of choosing the best approach of e-learning for implementation in the selected public university.

7.2 Summary of Results

In order to integrate PCs method in the comparison among several subjective weighting methods, the TROI method has been proposed to address the inconsistency problems through correcting the judgments in PC matrix. In this study,

twelve of PC matrices in PCs method were inconsistent. So, these matrices have been addressed by the proposed TROI method. Also, based on the proposal of the TROI method there is another pairwise comparisons technique called PC based on TROI method (PC-TROI) was proposed which help to reduce the number of comparisons among criteria.

In this research, the decision framework was developed on several subjective weighting methods for selection the optimal method. These methods were the chosen techniques, because the methods were commonly used in the previous studies. In particular, Rating (RM), Rank Order Centroid (ROC), Rank Exponent (RE), Rank Reciprocal (RR), Rank Sum (RS), Ratio (RW), Graphical Weights (GW), Direct Point Allocation (DPA), and Pairwise Comparisons (PCs) methods. In order to know how the decision framework was developed to select the optimal weights method, the absolute differences in each normalized weights from each method with the Ideal Weights (IW) for all methods have been calculated. Then, the smallest sum of the absolute difference means that this method is declared as the most accurate weights method. In this study, the GW method was declared as the optimal weights method to assign weights of e-learning criteria.

As a case study, the e-learning criteria were identified from previous studies, namely: Human resources, Specific ICT infrastructure for e-learning, Basic ICT infrastructure for e-learning, Strategic readiness for e-learning implementation, and Legal and formal readiness for e-learning implementation. In this study, the final criteria weights found that 'Strategic readiness for e-learning implementation' is the most important criterion by all groups of respondents as the aggregate weight appointed to

this criterion is 27.6 %. Furthermore, this study found out that the second most important criterion was 'human resources' with appointed weight equal to 26.5 %. Three criteria namely 'Legal and formal readiness for e-learning,' 'Specific ICT infrastructure for e-learning,' and 'Basic ICT infrastructure for e-learning' were given importance respectively with the calculated weights of 18.2 %, 14.2%, and 13.5%. These are illustrated in Section 6.4. The study has highlighted that this type of findings are new in its nature since there is a lack of study on the priority weights in comparing the different subjective weighting methods of e-learning criteria.

The result of the application of the decision framework in evaluating of e-learning approaches in a selected public university, the most suitable e-learning approach was the flipped classroom approach, and it is selected by all three groups (administrative, academic staff, and postgraduate students). Besides, the blended learning was the second most important based on the survey. ICT supported face-to-face learning, and synchronous learning were given the third and fourth importance respectively by the survey participants. At the same time, asynchronous learning was found the least important approach of e-learning as displayed in Table 6.23.

The study concludes that the selection of optimal weights method for criteria is crucial and should be give much attention by the researchers. This conclusion is based on survey outcomes of only 95 participants from the three groups (administrative, academic staff, and postgraduate students) took part in the survey. This study highlights that the optimal weights method found in this study may change if more or less number of respondents took part in our survey, as well as if the number of criteria is more or less than five. The results are valid for the selected university only.

7.3 Accomplishment of Research Objectives

This research successfully achieved all its objectives as described in Chapter One. The study has generated proposed decision framework in order to get an effective way to determine the optimal subjective weights method for avoiding inaccurate weights in solving MCDM problems. The following implications were arrived at to show the benefits of this research.

- I. The PCs in AHP method has inconsistency problem. So, in this study TROI method was proposed for rectifying the inconsistent judgments in PC matrix for achieving the first objective in this research. This proposed method enables us to check the consistency conveniently in the experts' viewpoints without a need of revised judgments from DMs. TROI method highlights that not only to address inconsistent indicators in PCs but also can be used to create a new process (PC-TROI) for the DM to deals with PCs easily, through reducing comparisons significantly. Based on TROI method, DM does not need to conduct comprehensive comparisons among all the criteria. But the DMs only makes $(n - 1)$ of comparisons among items by using 1 – 5 scale rather than Saaty's scale to avoid inconsistent cases especially when dealing with large number of criteria, where n refers to the number of items or criteria. In other words, the evaluator has less burden in making the pairwise comparison as compared what they have to do in the original PCs steps.
- II. The second objective achieved by proposed a decision framework for selecting the optimal weights method through comparison among several subjective weighting methods for criteria. This proposed decision framework can be used with several problems with regard to subjective weights methods

in order to get more accurate criteria weights in solving multi criteria problem. In this study, the GW method has been found to be the optimal weights method.

- III. Based on the application of proposed decision framework, all the criteria were weighted and ranked by the optimal weights method (GW method), and this set of weights were used in evaluating five approaches of e-learning by using TOPSIS method. The results based on the TOPSIS technique had shown that the flipped classroom approach is preferred by all the participants in the selected public university, and it will be recommended to the management of the university. Thus, this had ensured that the third purpose of the study was achieved in this research.

7.4 Contributions of the Research

This research has contributed modestly towards determining optimal weights to solve multi criteria problems. The discussion on the contribution of this research is divided into two aspects: the body of knowledge and contribution to higher learning institutions as described in the following subsections.

7.4.1 Body of Knowledge

The principal theoretical contribution of this research is in solving MCDM problems especially in selecting the optimal subjective weights method. Specifically, this study proposed a decision framework for evaluating the criteria through comparison of various subjective weights methods included PCs method in selecting the optimal weights method for the criteria. This study revealed that various weighting

techniques applied to the same problem had created a variety of weights attached to e-learning criteria. Various weighting method may yield different sets of weights that may have significant effects on the outcomes of any problem for solving any problem in any field. This study comes to suggest a decision framework to identify the optimal subjective weighting method for evaluating multi-criteria problems.

The AHP method is one of the subjective weighting methods, and it needs to check its consistency of judgments in PC matrix. For that, TROI method was proposed to rectify the inconsistent PCs in the AHP method. Besides, by TROI method a new procedure (PC-TROI) was also proposed. It can be used to create a new process for the DM to deals with PCs easily, through reducing comparisons significantly. For this reason, this study puts its main attention to explain TROI method in Chapter Five.

In this study, TOPSIS was used to evaluate five types of e-learning based on the optimal subjective weights. However, most of the researchers use TOPSIS technique with objective weighting methods involving cost and benefit. In this study, all criteria about e-learning were benefited criteria. That is why the positive ideal solution is the maximum (max) value, whereas the negative ideal solution is the minimum (min) value. The process was carried out by taking maximum values from each column as PIS, and once again taking minimum values from each column as NIS.

7.4.2 Contribution to Higher Learning Institutions

This study has given a clear picture for the leaderships at higher education towards using e-learning to enhance the education process. It contributes significantly to institutional planning towards implementation of e-learning in the higher education in response to the need for educational reform. It also aims to develop Malaysian's educational infrastructure through using of e-learning and information technology in education sector particularly in Malaysian universities. The study also showed that such implementation would contribute to the educational process and help the educational leaders to support and enhance the process in the educational institutions to save efforts, costs and time.

The problems and challenges concerning e-learning approaches occur on the state level, university, and faculty levels as well as on personal (teacher, student and staff) level. The problem of prioritization of e-learning approaches was solved with the help of multi-criteria modeling. By this MCDM techniques, the knowledge and preferences of all stakeholders were incorporated into the decision-making process. The result of this process was a recommendation to apply the flipped classroom approach as the most suitable option for implementing in the selected university.

7.5 Limitations of the Research

As in other studies, this study is bound to have a few limitations that are beyond the control of the researcher and can affect the study. The research is carried out with the constraints of time, place and resources. This study is limited in several ways. First, as a case study, this study carried out with the cooperation of the participants and

administration of the selected university who have agreed to provide the researcher with data. Second, this research is limited to only nine subjective weights methods to evaluate e-learning criteria because of its effect on the outcomes in solving multi criteria problems. Different techniques of weighting methods may give different ranking when applied to the same problem. Third, the study selected TOPSIS method to evaluate five e-learning approaches. However, if different methods are used in the evaluation, different results may reveal.

7.6 Recommendations and Future Work

As stated previously, data collection was performed only from a selected public university, hence, in the future, this can be extended for more than a university in Malaysia to obtain more stable results regarding the application of weights methods and their priority ranks. The current research provides a guideline or decision framework on how to choose the optimal weights method compared with the other weighting methods in order to get reliable weights. Therefore, further exploration can be made in the field based on the following recommendations:

- I. In this study, TROI method was introduced as the proposed method to solve inconsistency problems with PCs in AHP technique. In addition, PC-TROI is suggested that only the first criterion should be compared with the other criteria in PCs for further research. Therefore, there is no need to make comparisons among all the criteria.
- II. In this research, a decision framework was developed to select the optimal weights method. The application of the framework were applied by nine of subjective weighting methods (ROC, RE, RR, RS, RM, RW, DPA, GW, and

PCs methods) to analyze criteria weights about e-learning and select the optimal weights of those methods. For future studies, the proposed decision framework would apply to other fields. Therefore, this practice will additionally help DMs to select the optimal weights method for their decision-making process.

- III. The results of this weighting framework provide more consistent weight values that reflect true and real preferences by decision-maker. These values provide good input for subsequent optimization modeling such as in linear and goal programming.
- IV. In this study, samples were from administrative, academic staff and postgraduate students. Their knowledge or experience on real implementation related to e-learning may not be enough with high certainty in this field of research. Therefore, it is suggested to have more experienced people in e-learning criteria to get involved in the survey. The results for priority ranking of e-learning criteria will lead to a stable outcome and reality of the use of e-learning.
- V. E-learning criteria could be revisited to check whether any other essential criteria were not missing. Nevertheless, five criteria chosen for this research are reasonably numbered to decide which e-learning approach needs more attention for implementation in higher education.

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Appendix A

Questionnaire for E-Learning Implementation in UUM

Dear Sir/Madam,

First we should appreciate your kind willingness to participate in our academic survey. Title of research: SELECTION OF THE BEST SUBJECTIVE CRITERIA WEIGHTING METHOD FOR EVALUATING E-LEARNING MODELS. This survey aims to get your idea about e-learning implementation in university. We considered five major models of e-learning: 1) ICT supported traditional teaching, 2) flipped classroom, 3) blended learning, 4) synchronous learning and 5) asynchronous learning as the alternatives: and five factors or criteria about the e-learning. The research needs your judgment about the importance of e-learning models implementation and about factors (criteria) essential for decision making about the e-learning implementation. Therefore, kindly please indicate the importance of each item in the questionnaire via online. This survey needs your idea as a management expert at university, as an expert in teaching methods, as an expert in e-learning or interested in the implementation of e-learning in the university. Your answers will be treated with strict confidential and will be used for the purpose of the study. A brief description of the alternatives (e-learning models) and factors (criteria) are provided as in the following Appendices A and B. To start this process press on the link below or make copy the link and paste it in your URL page. We really appreciate your cooperation. Thank you. For more information about the study please read the attachment https://docs.google.com/forms/d/1ztIs-WOCnj4JYd4oGzwnITAIUoliqPUfPPVtp9fICVc/viewform?usp=send_form

Question-1 Statement: Please identify the MOST important e-learning criterion from the list below and give it a rating of 100. Next, rate each of the other criteria in turn on a scale of 10–90, to indicate how important they would be compared to the MOST important criterion in YOUR decision. For example, the most important criterion first and give a rating 100 to it. The rest of the criteria can be given 10–90 points according to their importance in e-learning implementation. A high rating score means that the criterion would be important.

Rating method

10 = least importance, 100 = most importance.

	10	20	30	40	50	60	70	80	90	100
Human resources	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Specific ICT infrastructure for e-learning	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Basic ICT infrastructure for e-learning	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Strategic readiness for e-learning implementation	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Legal and formal readiness for e-learning implementation	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Question-2 Statement: Please identify importance e-learning criteria from the list below and give it a rank of 1 to 5 in your decision.

Ranking of criteria

1= most importance, 2= important, 3= moderate importance, 4= low importance 5= least importance

	1	2	3	4	5
Human resources	☐	☐	☐	☐	☐
Specific ICT infrastructure for e-learning	☐	☐	☐	☐	☐
Basic ICT infrastructure for e-learning	☐	☐	☐	☐	☐
Strategic readiness for e-learning implementation	☐	☐	☐	☐	☐
Legal and formal readiness for e-learning implementation	☐	☐	☐	☐	☐

Question-3 Statement: Please identify the LEAST important criterion from the list below and give it a rating of 10. Next, consider each of the other criteria in turn and indicate how important they would be compared to the LEAST important criterion in your decision. All ratings should be greater than 10. (For example, if X was 3 times as important as Y which is the least important criterion, you would give X a rating of 30).

Ratio method

	10	20	30	40	50	60	70	80	90	100
Human resources	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Specific ICT infrastructure for e-learning	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Basic ICT infrastructure for e-learning	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Strategic readiness for e-learning implementation	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Legal and formal readiness for e-learning implementation	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Question-4 Statement: Please identify the important criterion from the list below and give it a rating of 5 to 100. The total of all factors (criteria) weights must be summed up to 100. For example, here we have five factors, you will give a score for all these factors, but the total should be 100.

Point Allocation weights method

	5	10	15	20	25	30	35	40	45	50	55	60	65	70	75	80	85	90	95	100
Human resources	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Specific ICT infrastructure for e-learning	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Basic ICT infrastructure for e-learning	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Strategic readiness for e-learning implementation	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Legal and formal readiness for e-learning implementation	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Question-5 Statement (Pairwise comparisons of criteria): Using the scale of 1 to 9 with a choice from equally important (1) to extremely important (9), please rate the following factors (criteria) with respect to their reciprocal criterion. For example, here we are comparing between the two factors (criteria) you will give a score to only one factor which be more important than another. If you give score 3 to criterion 1 compared with criterion 2 that means criterion 1 three times more important than criterion 2, and so on.

1 = Equal Importance, 2 = Equally to Moderately, 3 = Moderate Importance, 4 = Moderately to Strong, 5 = Strong Importance, 6 = Strongly to very strong, 7 = Very strong Importance, 8 = Very strong to extremely, 9 = Extreme Importance.

Respect criterion 1 with criterion 2 importance of e-learning

Please tick over the number 1-9 in a row. Give a score to only one of the criteria. Please tick over only one row which is more important than other.

	1	2	3	4	5	6	7	8	9
Human resources	☐	☐	☐	☐	☐	☐	☐	☐	☐
Specific ICT infrastructure for e-learning	☐	☐	☐	☐	☐	☐	☐	☐	☐

Respect criterion 1 with criterion 3 importance of e-learning

Please tick over the number 1-9 in a row. Give a score to only one of the criteria. Please tick over only one row which is more important than other.

	1	2	3	4	5	6	7	8	9
Human resources	☐	☐	☐	☐	☐	☐	☐	☐	☐
Basic ICT infrastructure for e-learning	☐	☐	☐	☐	☐	☐	☐	☐	☐

Respect criterion 1 with criterion 4 importance of e-learning

Please tick over the number 1-9 in a row. Give a score to only one of the criteria. Please tick over only one row which is more important than other.

	1	2	3	4	5	6	7	8	9
Human resources	☐	☐	☐	☐	☐	☐	☐	☐	☐
Strategic readiness for e-learning implementation	☐	☐	☐	☐	☐	☐	☐	☐	☐

Respect criterion 1 with criterion 5 importance of e-learning

Please tick over the number 1-9 in a row. Give a score to only one of the criteria. Please tick over only one row which is more important than other.

	1	2	3	4	5	6	7	8	9
Human resources	☐	☐	☐	☐	☐	☐	☐	☐	☐
Legal and formal readiness for e-learning implementation	☐	☐	☐	☐	☐	☐	☐	☐	☐

Respect criterion 2 with criterion 3 importance of e-learning

Please tick over only one row which is more important than other.

	1	2	3	4	5	6	7	8	9
Specific ICT infrastructure for e-learning	☐	☐	☐	☐	☐	☐	☐	☐	☐
Basic ICT infrastructure for e-learning	☐	☐	☐	☐	☐	☐	☐	☐	☐

Respect criterion 2 with criterion 4 importance of e-learning

Please tick over only one row which is more important than other.

	1	2	3	4	5	6	7	8	9
Specific ICT infrastructure for e-learning	☐	☐	☐	☐	☐	☐	☐	☐	☐
Strategic readiness for e-learning implementation	☐	☐	☐	☐	☐	☐	☐	☐	☐

Respect criterion 2 with criterion 5 importance of e-learning

Please tick over only one row which is more important than other.

	1	2	3	4	5	6	7	8	9
Specific ICT infrastructure for e-learning	☐	☐	☐	☐	☐	☐	☐	☐	☐
Legal and formal readiness for e-learning implementation	☐	☐	☐	☐	☐	☐	☐	☐	☐

Respect criterion 3 with criterion 4 importance of e-learning

Please tick over only one row which is more important than other.

	1	2	3	4	5	6	7	8	9
Basic ICT infrastructure for e-learning	☐	☐	☐	☐	☐	☐	☐	☐	☐
Strategic readiness for e-learning implementation	☐	☐	☐	☐	☐	☐	☐	☐	☐

Respect criterion 3 with criterion 5 importance of e-learning

Please tick over only one row which is more important than other.

	1	2	3	4	5	6	7	8	9
Basic ICT infrastructure for e-learning	☐	☐	☐	☐	☐	☐	☐	☐	☐
Legal and formal readiness for e-learning implementation	☐	☐	☐	☐	☐	☐	☐	☐	☐

Respect criterion 4 with criterion 5 importance of e-learning

Please tick over only one row which is more important than other.

	1	2	3	4	5	6	7	8	9
Strategic readiness for e-learning implementation	☐	☐	☐	☐	☐	☐	☐	☐	☐
Legal and formal readiness for e-learning implementation	☐	☐	☐	☐	☐	☐	☐	☐	☐

Question-6 Statement: Please evaluate the importance of each criterion for each e-learning model from the list below and give it a rating of 10 to 100 in your decision. Here we have five models of e-learning. You will give a score about the importance for each model with respect to each criterion. For example, when comparing the e-learning models with the importance of criterion 1 for each model, if you will give 90 to flipped classroom, 40 to blended learning, 60 to ICT supported face-to-face learning, 30 to synchronous learning and 50 to asynchronous learning, that means the criterion 1 is the most important with flipped classroom and less important with synchronous learning.

Respect the e-learning models with criterion 1

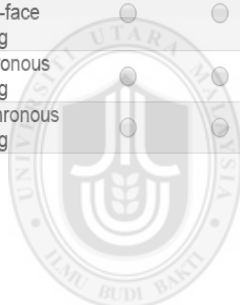
Respect e-learning implementation with Human resources

	10	20	30	40	50	60	70	80	90	100
Flipped classroom	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Blended learning	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
ICT supported face-to-face learning	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Synchronous learning	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Asynchronous learning	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Respect the e-learning models with criterion 2

Respect e-learning implementation with specific ICT infrastructure for e-learning

	10	20	30	40	50	60	70	80	90	100
Flipped classroom	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Blended learning	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
ICT supported face-to-face learning	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Synchronous learning	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Asynchronous learning	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐



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Respect the e-learning models with criterion 3

Respect e-learning implementation with basic ICT infrastructure for e-learning

	10	20	30	40	50	60	70	80	90	100
Flipped classroom	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Blended learning	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
ICT supported face-to-face learning	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Synchronous learning	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Asynchronous learning	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Respect the e-learning models with criterion 4

Respect e-learning implementation with strategic readiness for e-learning implementation

	10	20	30	40	50	60	70	80	90	100
Flipped classroom	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Blended learning	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
ICT supported face-to-face learning	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Synchronous learning	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Asynchronous learning	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Respect the e-learning models with criterion 5

Respect e-learning implementation with legal and formal readiness for e-learning implementation

	10	20	30	40	50	60	70	80	90	100
flipped classroom	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
blended learning	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
ICT supported face-to-face learning	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
synchronous learning	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
asynchronous learning	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Appendix B

Collecting Data from Administrative Group (Group1)

In group 1, 22 participants (P1, P2... P22) from administrative in were answered the questions for five e-learning criteria (CR1, CR2... CR5).

1- Data Collected for Rating Method

Administrative data for Rating method													
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13
CR1	100	40	50	70	60	100	50	40	80	90	70	100	60
CR2	40	70	80	30	30	40	70	50	40	80	100	30	40
CR3	70	80	100	40	40	30	40	60	30	100	90	50	30
CR4	80	100	70	80	80	60	100	80	100	70	80	60	100
CR5	90	30	40	100	100	80	60	100	70	60	60	80	80
	P14	P15	P16	P17	P18	P19	P20	P21	P22				
CR1	80	100	70	60	70	50	80	100	90				
CR2	50	60	50	50	40	30	50	50	30				
CR3	30	40	30	20	20	70	60	70	60				
CR4	70	70	90	100	100	100	100	80	100				
CR5	100	80	100	80	60	90	30	30	80				

2- Data Collected for Ranking Method

Administrative data for Ranking method													
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13
CR1	1	4	4	3	3	1	4	5	2	2	4	1	3
CR2	5	3	2	5	5	4	2	4	4	3	1	5	4
CR3	4	2	1	4	4	5	5	3	5	1	2	4	5
CR4	3	1	3	2	2	3	1	2	1	4	3	3	1
CR5	2	5	5	1	1	2	3	1	3	5	5	2	2
	P14	P15	P16	P17	P18	P19	P20	P21	P22				
CR1	2	1	3	3	2	4	2	1	2				
CR2	4	4	4	4	4	5	4	4	5				
CR3	5	5	5	5	5	3	3	3	4				
CR4	3	3	2	1	1	1	1	2	1				
CR5	1	2	1	2	3	2	5	5	3				

3- Data Collected for Ratio Method

Administrative data for Ratio method													
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13
CR1	80	30	30	50	50	60	40	10	80	70	30	90	60
CR2	10	50	70	10	10	30	60	30	20	50	100	10	40
CR3	30	60	60	30	30	10	10	40	10	90	70	30	10
CR4	60	70	90	60	70	50	80	50	90	30	50	50	70
CR5	70	10	10	80	90	80	50	70	60	10	10	70	90
	P14	P15	P16	P17	P18	P19	P20	P21	P22				
CR1	70	90	50	50	60	40	70	90	60				
CR2	40	40	30	30	30	10	30	30	10				
CR3	10	10	10	10	10	50	40	40	30				
CR4	60	60	70	90	80	80	80	70	80				
CR5	90	70	90	70	50	70	10	10	50				

4- Data Collected for Point Allocation Method

Administrative data for Point allocation method													
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13
CR1	30	10	10	20	20	35	15	10	15	25	15	35	20
CR2	10	20	25	10	5	10	25	15	25	15	35	5	10
CR3	15	30	35	15	10	5	10	20	10	45	25	10	5
CR4	20	35	25	20	25	20	30	25	30	10	20	20	35
CR5	25	5	5	35	40	30	20	30	20	5	5	30	25
	P14	P15	P16	P17	P18	P19	P20	P21	P22				
CR1	25	40	20	20	25	15	30	30	30				
CR2	10	10	15	15	15	5	10	15	5				
CR3	5	5	5	5	5	20	20	20	10				
CR4	20	20	25	35	35	35	35	25	40				
CR5	40	25	35	25	20	25	5	10	15				

5- Data Collected for Pairwise Comparisons and Graphical Methods

P1					P2				
1	8	6	4	2	1	0.33	0.25	0.2	2
0.12	1	0.5	0.33	0.2	3	1	0.33	0.33	4
0.17	2	1	0.5	0.33	4	3	1	0.5	5
0.25	3	2	1	0.5	5	3	2	1	6
0.5	5	3	2	1	0.5	0.25	2	0.17	1
P3					P4				
1	2	0.33	0.25	3	1	3	2	0.33	0.25
0.5	1	0.2	0.33	6	0.33	1	0.5	0.2	0.14
3	5	1	0.33	5	0.5	2	1	0.33	0.17
4	3	3	1	3	3	5	3	1	0.5
0.33	0.17	0.2	0.33	1	4	7	6	2	1
P5					P6				
1	4	3	0.33	0.2	1	5	7	4	2
0.25	1	0.5	0.2	0.14	0.2	1	3	0.33	0.25
0.33	2	1	0.25	0.17	0.14	0.33	1	0.2	0.17
3	5	4	1	3	0.25	3	5	1	0.33
5	7	6	0.33	1	0.5	4	6	3	1
P7					P8				
1	0.33	2	0.2	0.5	1	0.5	0.33	0.25	0.2
3	1	5	2	0.5	2	1	0.5	0.25	0.2
0.5	0.2	1	0.14	0.25	3	2	1	0.5	0.33
5	0.5	7	1	3	4	4	2	1	0.5
2	2	4	0.33	1	5	5	3	2	1
P9					P10				
1	3	4	0.5	2	1	3	0.5	3	4
0.33	1	3	0.2	2	0.33	1	0.25	3	4
0.25	0.33	1	0.14	0.25	2	4	1	5	7
2	5	7	1	5	0.33	0.33	0.2	1	3
0.5	2	4	0.2	1	0.25	0.25	0.14	0.33	1
P11					P12				
1	0.14	0.25	0.5	2	1	7	5	3	2
7	1	3	5	9	0.14	1	0.5	0.33	0.2
4	0.33	1	2	6	0.2	2	1	0.5	0.25
2	0.2	0.5	1	4	0.33	3	2	1	0.5
0.5	0.11	0.17	0.25	1	0.5	5	4	2	1
P13					P14				
1	0.5	0.33	5	2	1	0.33	0.25	0.5	2
2	1	0.33	4	4	3	1	0.33	3	0.2
3	3	1	6	5	4	3	1	0.33	0.14
0.2	0.25	0.17	1	0.5	2	0.33	3	1	0.25
0.5	0.25	0.2	2	1	0.5	5	7	4	1
P15					P16				
1	5	7	4	2	1	3	5	0.33	0.2
0.2	1	3	0.25	0.2	0.33	1	2	0.25	0.17
0.14	0.33	1	0.2	0.17	0.2	0.5	1	2	0.12
0.25	4	5	1	0.5	3	4	5	1	0.33
0.5	5	6	2	1	5	6	8	3	1

P17					P18				
1	3	5	0.2	0.33	1	3	5	0.33	2
0.33	1	2	0.17	0.25	0.33	1	3	2	3
0.2	0.5	1	0.12	3	0.2	0.33	1	5	7
5	6	8	1	0.33	3	0.5	0.2	1	3
3	4	0.33	3	1	0.5	0.33	0.14	0.33	1
P19					P20				
1	3	0.5	0.25	0.33	1	4	3	0.5	6
0.33	1	0.25	0.14	0.17	0.25	1	0.5	0.2	2
2	4	1	0.33	0.5	0.33	2	1	0.25	3
4	7	3	1	2	2	5	4	1	7
3	6	2	0.5	1	0.17	0.5	0.33	0.14	1
P21					P22				
1	6	5	2	8	1	5	3	0.5	2
0.17	1	0.5	0.25	2	0.2	1	0.5	0.14	0.25
0.2	2	1	0.33	3	0.33	2	1	0.2	0.5
0.5	4	3	1	6	2	7	5	1	3
0.12	0.5	0.33	0.17	1	0.5	4	2	0.33	1

6- Data Collected for TOPSIS Method

Administrative data for TOPSIS method										
P1					P2					
CR1	CR2	CR3	CR4	CR5		CR1	CR2	CR3	CR4	CR5
80	90	60	70	70	A1	40	40	60	70	50
70	80	70	60	50	A2	50	30	50	60	40
90	70	100	80	90	A3	30	50	80	80	60
40	50	50	40	40	A4	30	20	40	40	30
20	30	40	30	30	A5	20	10	30	20	20
P3					P4					
60	70	70	80	50	A1	80	80	60	60	80
50	50	40	70	60	A2	60	50	70	50	50
80	90	60	90	40	A3	100	70	80	80	60
30	30	50	50	70	A4	40	40	50	40	40
20	10	30	30	90	A5	30	30	30	20	30
P5					P6					
70	80	50	80	80	A1	60	80	80	60	90
80	60	40	70	60	A2	50	70	60	70	60
100	70	60	90	70	A3	80	90	100	80	70
50	40	30	60	50	A4	30	60	40	50	40
30	30	20	50	40	A5	20	50	30	30	30
P7					P8					
70	90	80	70	70	A1	70	90	70	70	70
60	80	60	50	80	A2	60	80	60	50	50
80	100	70	80	90	A3	80	100	90	80	90
30	40	30	30	50	A4	30	40	40	30	30
20	30	20	20	30	A5	20	30	30	20	10
P9					P10					

80	90	80	80	70	A1	90	90	90	90	90
70	60	90	70	60	A2	80	80	80	80	80
100	70	70	60	90	A3	100	100	100	100	100
40	30	60	50	30	A4	70	70	70	70	70
30	20	50	40	20	A5	60	60	60	60	60
P11						P12				
CR1	CR2	CR3	CR4	CR5		CR1	CR2	CR3	CR4	CR5
70	70	90	80	70	A1	80	70	70	70	80
100	60	80	50	80	A2	60	60	50	60	60
60	90	70	60	100	A3	100	90	90	90	100
90	30	50	40	50	A4	40	30	40	30	40
80	20	30	20	40	A5	30	20	30	20	30
P13						P14				
80	70	80	70	90	A1	70	80	80	70	80
50	60	60	40	70	A2	50	60	60	60	60
90	90	90	80	100	A3	90	100	90	80	90
40	40	30	30	50	A4	40	50	50	30	40
30	30	20	20	40	A5	30	40	40	20	30
P15						P16				
80	80	80	80	80	A1	70	80	70	80	70
70	60	70	60	50	A2	60	60	60	70	50
100	90	90	90	90	A3	90	100	90	100	90
30	30	40	40	40	A4	40	50	30	20	30
20	10	30	20	20	A5	30	40	20	10	20
P17						P18				
90	70	60	80	80	A1	80	90	70	90	60
70	60	50	60	70	A2	70	60	60	70	50
100	90	80	90	100	A3	100	100	90	100	90
40	30	30	20	30	A4	30	50	40	40	30
30	20	20	10	20	A5	20	30	30	20	10
P19						P20				
90	90	90	90	70	A1	80	80	80	70	90
70	70	70	60	50	A2	70	60	60	50	70
80	80	80	80	90	A3	100	70	70	90	100
40	40	40	40	30	A4	50	40	40	30	50
30	30	30	20	20	A5	40	30	30	20	40
P21						P22				
80	90	80	70	90	A1	80	80	90	80	80
90	80	70	60	80	A2	70	60	80	70	70
70	70	60	90	100	A3	60	70	70	100	90
50	50	40	40	50	A4	50	40	50	50	60
40	40	30	30	40	A5	40	30	40	40	50

Appendix C

Collecting Data from Academic Staff Group (Group 2)

In group 2, 38 participants (P1, P2... P38) from academic staff in UUM were answered the questions for five e-learning criteria (CR1, CR2... CR5).

1- Data Collected for Rating Method

Academic staff data for Rating method													
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13
CR1	70	100	90	60	50	90	90	90	80	70	80	50	60
CR2	60	60	80	70	80	100	80	100	90	60	100	60	50
CR3	50	50	60	100	100	70	100	60	50	100	70	80	100
CR4	100	70	70	80	70	80	60	50	60	80	50	100	40
CR5	80	80	100	50	60	60	70	80	100	90	30	30	80
	P14	P15	P16	P17	P18	P19	P20	P21	P22	P23	P24	P25	P26
CR1	80	100	60	70	80	100	30	80	100	80	60	100	70
CR2	60	40	40	90	90	90	50	60	80	100	40	80	60
CR3	50	50	80	80	100	80	70	100	70	90	30	60	30
CR4	40	80	30	60	70	70	90	90	60	70	100	40	100
R5	100	60	100	100	60	60	100	40	40	60	80	30	80
	P27	P28	P29	P30	P31	P32	P33	P34	P35	P36	P37	P38	
CR1	90	80	80	100	100	70	100	90	90	100	70	80	
CR2	50	100	70	50	40	80	50	70	60	40	50	40	
CR3	30	90	50	20	20	90	70	50	30	60	40	100	
CR4	100	70	60	80	70	100	80	80	100	70	100	90	
CR5	70	60	100	90	90	60	20	100	70	80	80	60	

2- Data Collected for Ranking Method

Academic staff data for Ranking method													
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13
CR1	3	1	2	4	5	2	2	2	3	4	2	4	3
CR2	4	4	3	3	2	1	3	1	2	5	1	3	4
CR3	5	5	5	1	1	4	1	4	5	1	3	2	1
CR4	1	3	4	2	3	3	5	5	4	3	4	1	5
CR5	2	2	1	5	4	5	4	3	1	2	5	5	2
	P14	P15	P16	P17	P18	P19	P20	P21	P22	P23	P24	P25	P26
CR1	2	1	3	4	3	1	5	3	1	3	3	1	3
CR2	3	5	4	2	2	2	4	4	2	1	4	2	4
CR3	5	4	2	3	1	3	3	1	3	2	5	3	5
CR4	4	2	5	5	4	4	2	2	4	4	1	4	1
CR5	1	3	1	1	5	5	1	5	5	5	2	5	2
	P27	P28	P29	P30	P31	P32	P33	P34	P35	P36	P37	P38	
CR1	2	3	2	1	1	4	1	2	2	1	3	3	
CR2	4	1	3	4	4	3	4	4	4	5	4	5	
CR3	5	2	5	5	5	2	3	5	5	4	5	1	
CR4	1	4	4	3	3	1	2	3	1	3	1	2	
CR5	3	5	1	2	2	5	5	1	3	2	2	4	

3- Data Collected for Ratio Method

Academic staff data for Ratio method													
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13
CR1	90	80	80	30	10	90	70	70	70	40	60	30	50
CR2	40	20	50	50	80	100	60	80	80	10	80	50	30
CR3	10	10	10	70	100	30	80	20	10	100	50	60	80
CR4	60	30	40	60	50	50	10	10	30	70	30	80	10
CR5	80	70	90	10	40	10	40	50	90	80	10	10	60
	P14	P15	P16	P17	P18	P19	P20	P21	P22	P23	P24	P25	P26
CR1	60	80	60	40	50	80	10	60	90	70	50	90	50
CR2	50	10	20	70	70	60	30	40	80	90	30	70	30
CR3	10	40	70	60	80	50	50	100	60	80	10	50	10
CR4	30	60	10	10	30	30	60	70	30	50	90	30	80
CR5	80	50	80	100	10	10	80	10	10	10	70	10	60

	P27	P28	P29	P30	P31	P32	P33	P34	P35	P36	P37	P38
CR1	70	50	60	80	90	40	80	70	70	80	60	50
CR2	40	90	50	30	40	60	30	30	40	10	40	10
CR3	10	70	10	10	10	70	50	10	10	40	10	70
CR4	80	30	40	60	50	90	70	50	90	60	80	60
CR5	50	10	70	70	70	10	10	90	60	70	70	20

4- Data Collected for Point Allocation Method

Academic staff data for point allocation method													
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13
CR1	25	45	30	15	10	25	25	30	20	15	30	15	20
CR2	10	5	20	20	25	30	20	35	25	5	40	20	15
CR3	5	5	5	30	40	15	30	10	5	30	15	25	30
CR4	35	20	10	25	15	20	10	5	10	20	10	35	10
CR5	25	25	35	10	10	10	15	20	40	30	5	5	25
	P14	P15	P16	P17	P18	P19	P20	P21	P22	P23	P24	P25	P26
CR1	25	40	25	10	15	45	5	20	35	20	20	35	20
CR2	20	10	5	15	25	15	15	25	40	15	30	10	
CR3	10	10	30	20	40	15	20	35	20	25	5	20	5
CR4	15	25	5	25	10	10	25	25	15	10	35	10	35
CR5	30	15	35	30	10	5	35	5	5	5	25	5	30
	P27	P28	P29	P30	P31	P32	P33	P34	P35	P36	P37	P38	
CR1	20	20	30	35	35	15	40	30	30	45	20	20	
CR2	15	35	20	15	15	20	10	10	10	5	10	10	
CR3	10	25	5	5	5	20	15	5	5	10	5	30	
CR4	40	15	10	20	20	40	30	20	35	15	35	25	
CR5	15	5	35	25	25	5	5	35	20	25	30	15	

5- Data Collected for Pairwise Comparisons and Graphical Methods

Academic staff data for Pairwise Comparison method									
P1					P2				
1	2	0.2	0.25	0.5	1	8	5	3	2
0.5	1	0.14	0.17	0.33	0.12	1	0.5	0.33	0.2
5	7	1	2	3	0.2	2	1	0.5	0.25
4	6	0.5	1	3	0.33	3	2	1	0.5
2	3	0.33	0.33	1	0.5	5	4	2	1
P3					P4				
1	0.14	0.17	0.33	0.2	1	2	0.5	0.33	3
7	1	3	5	4	0.5	1	0.33	0.2	2
6	0.33	1	3	2	2	3	1	0.5	0.17
3	0.2	0.33	1	0.5	3	5	2	1	8
5	0.25	0.5	2	1	0.33	0.5	6	0.12	1
P5					P6				
1	0.5	2	3	0.33	1	0.5	3	2	5
2	1	3	5	0.5	2	1	5	3	7
0.5	0.33	1	2	0.5	0.33	0.2	1	0.5	2
0.33	0.2	0.5	1	0.14	0.5	0.33	2	1	3
3	2	5	7	1	0.2	0.14	0.5	0.33	1
P7					P8				
1	0.33	0.5	2	0.33	1	0.5	5	3	4
3	1	2	5	7	2	1	7	3	5
2	0.5	1	4	5	0.2	0.14	1	0.33	0.5
0.5	0.2	0.25	1	2	0.33	0.33	3	1	2
3	0.14	0.2	0.5	1	0.25	0.2	2	0.5	1
P9					P10				
1	0.2	0.14	0.5	0.33	1	0.33	0.5	0.2	0.25
5	1	0.5	4	0.33	3	1	2	0.33	0.5
7	2	1	5	3	2	0.5	1	0.2	0.33
2	0.25	0.2	1	0.5	5	3	5	1	2
3	3	0.33	2	1	4	2	3	0.5	1
P11					P12				
1	0.33	4	5	7	1	0.5	0.33	0.2	2
3	1	3	5	6	2	1	0.25	0.2	3
0.25	0.33	1	3	4	3	4	1	0.33	4
0.2	0.2	0.33	1	3	5	5	3	1	7
0.14	0.17	0.25	0.33	1	0.5	0.33	0.25	0.14	1
P13					P14				
1	3	0.2	2	0.17	1	3	5	4	0.33
0.33	1	0.14	2	0.33	0.33	1	4	2	0.2
5	7	1	7	3	0.2	0.25	1	0.5	0.14
0.5	0.5	0.14	1	0.12	0.25	0.5	2	1	0.2
6	3	0.33	8	1	3	5	7	5	1
P15					P16				
1	7	5	2	3	1	2	0.5	3	0.25
0.14	1	2	3	0.25	0.5	1	0.33	2	0.14
0.2	0.5	1	0.33	0.33	2	3	1	5	0.33
0.5	0.33	3	1	3	0.33	0.5	0.2	1	0.14
0.33	4	3	0.33	1	4	7	3	7	1
P17					P18				

1	0.2	0.3	0.5	0.14	1	0.5	0.33	2	4
5	1	2	3	0.5	2	1	0.5	4	6
3	0.5	1	2	0.33	3	2	1	5	7
2	0.33	0.5	1	0.2	0.5	0.25	0.2	1	2
7	2	3	5	1	0.25	0.17	0.14	0.5	1
P19					P20				
1	2	3	5	7	1	0.5	0.25	0.2	0.14
0.5	1	2	3	5	2	1	0.5	0.33	0.2
0.33	0.5	1	2	4	4	2	1	0.5	0.33
0.2	0.33	0.5	1	2	5	3	2	1	2
0.14	0.2	0.25	0.5	1	7	5	3	0.5	1
P21					P22				
1	2	0.25	0.5	5	1	2	3	5	7
0.5	1	0.17	0.33	3	0.5	1	2	4	5
4	6	1	3	9	0.33	0.5	1	3	5
2	3	0.33	1	6	0.2	0.25	0.33	1	2
0.2	0.33	0.11	0.17	1	0.14	0.2	0.2	0.5	1
P23					P24				
1	0.5	0.5	2	5	1	2	3	0.14	2
2	1	2	4	8	0.5	1	3	0.25	0.33
2	0.5	1	3	7	0.33	0.33	1	0.14	0.2
0.5	0.25	0.33	1	4	7	4	7	1	0.33
0.2	0.12	0.14	0.25	1	0.5	3	5	3	1
P25					P26				
1	3	4	5	6	1	0.5	0.33	4	2
0.33	1	3	4	5	2	1	0.33	5	3
0.25	0.33	1	2	4	3	3	1	6	3
0.2	0.25	0.5	1	2	0.25	0.2	0.17	1	0.33
0.17	0.2	0.25	0.5	1	0.5	0.33	0.33	3	1
P27					P28				
1	4	6	0.5	3	1	0.25	0.5	2	4
0.25	1	3	0.2	0.5	4	1	2	6	8
0.17	0.33	1	0.14	0.25	2	0.5	1	4	6
2	5	7	1	0.33	0.5	0.17	0.25	1	2
0.33	2	4	3	1	0.25	0.12	0.17	0.5	1
P29					P30				
1	2	5	2	0.5	1	5	6	2	3
0.5	1	4	2	0.5	0.2	1	2	0.33	0.25
0.2	0.25	1	0.33	0.17	0.17	0.5	1	0.2	0.17
0.5	0.5	3	1	0.33	0.5	3	5	1	0.5
2	2	6	3	1	0.33	4	6	2	1
P31					P32				
1	5	7	3	2	1	0.5	0.33	0.2	3
0.2	1	3	0.25	0.33	2	1	0.5	0.33	5
0.14	0.33	1	0.2	0.2	3	2	1	0.5	6
0.33	4	5	1	0.33	5	3	2	1	7
0.5	3	5	3	1	0.33	0.2	0.17	0.14	1
P33					P34				
1	5	3	2	7	1	4	6	2	0.5
0.2	1	0.5	0.25	2	0.25	1	2	0.5	0.14
0.33	2	1	0.5	4	0.17	0.5	1	0.25	0.12
0.5	4	2	1	6	0.5	2	4	1	0.25
0.14	0.5	0.25	0.17	1	2	7	8	4	1

P35					P36				
1	3	6	0.5	2	1	7	4	2	2
0.33	1	3	0.2	0.5	0.14	1	0.33	0.2	0.1
0.17	0.33	1	0.12	0.2	0.25	3	1	0.5	0.3
2	5	8	1	3	0.5	5	2	1	0.5
0.5	2	5	0.33	1	0.5	6	3	2	1
P37					P38				
1	2	5	0.5	0.5	1	4	0.5	0.5	3
0.5	1	3	0.25	0.33	0.25	1	0.17	0.2	0.5
0.2	0.33	1	0.14	0.17	2	6	1	2	5
2	4	7	1	2	2	5	0.5	1	4
2	3	6	0.5	1	0.33	2	0.2	0.25	1



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6- Data Collected for TOPSIS Method

Academic staff data for TOPSIS method										
P1						P2				
CR1	CR2	CR3	CR4	CR5		CR1	CR2	CR3	CR4	CR5
80	90	60	70	70	A1	40	40	60	70	50
70	80	70	60	50	A2	50	30	50	60	40
90	70	100	80	90	A3	30	50	80	80	60
40	50	50	40	40	A4	30	20	40	40	30
20	30	40	30	30	A5	20	10	30	20	20
P3						P4				
60	70	70	80	50	A1	80	80	60	60	80
50	50	40	70	60	A2	60	50	70	50	50
80	90	60	90	40	A3	100	70	80	80	60
30	30	50	50	70	A4	40	40	50	40	40
20	10	30	30	90	A5	30	30	30	20	30
P5						P6				
70	80	50	80	80	A1	60	80	80	60	90
80	60	40	70	60	A2	50	70	60	70	60
100	70	60	90	70	A3	80	90	100	80	70
50	40	30	60	50	A4	30	60	40	50	40
30	30	20	50	40	A5	20	50	30	30	30
P7						P8				
70	90	80	70	70	A1	70	90	70	70	70
60	80	60	50	80	A2	60	80	60	50	50
80	100	70	80	90	A3	80	100	90	80	90
30	40	30	30	50	A4	30	40	40	30	30
20	30	20	20	30	A5	20	30	30	20	10
P9						P10				
80	90	80	80	70	A1	90	90	90	90	90
70	60	90	70	60	A2	80	80	80	80	80
100	70	70	60	90	A3	100	100	100	100	100
40	30	60	50	30	A4	70	70	70	70	70
30	20	50	40	20	A5	60	60	60	60	60
P11						P12				
60	70	80	60	80	A1	60	70	80	70	60
60	50	70	40	50	A2	50	50	50	60	40
70	90	100	80	90	A3	70	90	60	100	80
40	30	40	20	40	A4	40	30	40	50	30

30	20	20	10	20	A5	30	20	30	30	20
P13						P14				
70	60	80	70	70	A1	80	70	80	80	60
80	50	50	60	50	A2	60	50	60	50	50
90	70	60	90	60	A3	90	60	90	60	90
60	40	40	70	60	A4	50	40	50	40	40
50	30	30	50	40	A5	30	20	30	30	30
P15						P16				
70	80	80	60	80	A1	80	80	80	70	60
60	50	70	50	70	A2	70	70	70	50	80
50	70	90	90	100	A3	100	90	60	80	90
40	40	40	30	30	A4	30	40	40	20	40
30	30	30	20	20	A5	20	20	30	10	30
P17						P18				
70	70	80	90	90	A1	70	90	90	70	50
80	90	90	90	90	A2	90	100	90	50	40
90	50	50	60	40	A3	60	80	90	70	60
60	90	90	60	90	A4	50	60	90	70	50
60	70	70	50	30	A5	40	70	90	70	40
P19						P20				
90	100	90	100	100	A1	90	90	90	90	90
60	90	90	100	90	A2	90	90	90	90	90
90	90	90	90	90	A3	90	90	90	90	90
90	100	90	90	100	A4	90	90	90	90	90
100	90	100	100	100	A5	90	90	90	90	90
P21						P22				
100	100	100	80	30	A1	70	70	90	90	80
90	80	80	60	80	A2	80	90	90	90	80
60	60	40	100	20	A3	100	100	100	90	80
80	30	70	70	50	A4	50	90	90	90	70
10	10	20	20	10	A5	80	90	90	80	70
P23						P24				
90	90	90	80	70	A1	80	70	80	70	60
80	80	80	60	60	A2	50	60	70	60	70
100	100	100	70	80	A3	90	100	100	90	90
70	70	70	50	50	A4	40	40	40	30	40
60	60	60	40	40	A5	30	30	30	20	30
P25						P26				
70	70	70	70	60	A1	70	80	70	70	80
60	40	50	50	50	A2	60	60	50	50	70

80	90	90	80	80	A3	90	90	100	90	100
50	30	40	40	30	A4	40	50	40	40	40
40	20	30	30	20	A5	30	40	30	30	30
P27						P28				
70	80	80	80	70	A1	100	90	90	90	80
60	60	70	60	50	A2	80	80	90	90	80
90	90	100	90	80	A3	90	100	90	90	80
20	40	40	40	30	A4	70	70	80	80	70
10	30	30	30	20	A5	60	60	80	80	70
P29						P30				
100	80	80	80	80	A1	60	90	90	70	80
70	70	70	70	70	A2	80	50	60	60	40
80	90	90	90	90	A3	90	70	70	100	70
60	60	60	60	60	A4	40	30	50	30	30
50	50	50	50	50	A5	20	20	30	20	20
P31						P32				
70	80	90	80	70	A1	80	80	08	80	80
80	50	60	50	40	A2	50	70	70	70	70
100	90	70	70	100	A3	60	90	90	90	90
30	30	30	30	20	A4	40	60	60	60	60
20	20	20	20	10	A5	30	50	50	50	50
P33						P34				
70	70	80	80	80	A1	80	70	70	80	80
60	80	90	60	70	A2	60	80	80	60	60
80	60	70	100	90	A3	70	50	60	70	100
50	40	50	50	60	A4	40	40	50	40	40
40	30	40	40	50	A5	30	30	30	30	30
P35						P36				
80	90	90	70	90	A1	80	80	80	60	80
70	70	60	60	60	A2	60	70	90	50	70
90	80	80	90	100	A3	70	60	60	80	90
30	50	50	40	40	A4	40	50	40	30	60
20	40	40	30	30	A5	30	40	30	20	50
P37						P38				
80	80	90	80	70	A1	80	80	70	80	70
60	60	80	70	60	A2	90	70	80	70	50
70	70	60	100	90	A3	70	60	50	100	90
50	50	40	50	40	A4	50	40	40	50	40
40	40	30	40	30	A5	40	30	30	40	30

Appendix D

Collecting Data from Postgraduate Students Group (Group3)

In group 3, 35 participants (P1, P2... P35) from postgraduate students in UUM were answered the questions for five e-learning criteria (CR1, CR2... CR5).

1- Data Collected for Rating Method

Post graduate students data for Rating method													
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13
CR1	100	100	60	60	50	60	50	70	90	100	80	100	100
CR2	90	30	30	40	40	30	30	60	60	50	50	60	70
CR3	80	50	40	30	30	100	90	40	30	30	20	40	60
CR4	70	20	90	100	100	50	100	100	100	90	90	90	80
CR5	60	70	100	80	70	80	70	90	80	70	100	70	50
	P14	P15	P16	P17	P18	P19	P20	P21	P22	P23	P24	P25	P26
CR1	100	80	90	70	100	100	100	100	80	100	70	100	100
CR2	50	40	60	60	30	80	40	70	60	30	60	40	40
CR3	40	60	40	50	50	70	30	30	50	50	40	60	20
CR4	70	100	100	100	70	90	70	80	100	70	100	90	80
CR5	30	70	70	30	60	50	60	50	30	60	30	70	70
	P27	P28	P29	P30	P31	P32	P33	P34	P35				
CR1	90	70	80	100	70	100	60	80	90				
CR2	70	40	60	60	50	40	20	20	100				
CR3	50	20	40	30	40	60	40	50	50				
CR4	100	100	100	80	100	70	100	100	80				
CR5	20	50	90	90	80	80	70	70	70				

2- Data Collected for Ranking Method

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13
CR1	1	1	3	3	3	3	4	3	2	1	3	1	1
CR2	2	4	5	4	4	5	5	4	4	4	4	4	3
CR3	3	3	4	5	5	1	2	5	5	5	5	5	4
CR4	4	5	2	1	1	4	1	1	1	2	2	2	2
CR5	5	2	1	2	2	2	3	2	3	3	1	3	5
	P14	P15	P16	P17	P18	P19	P20	P21	P22	P23	P24	P25	P26
CR1	1	2	2	2	1	1	1	1	2	1	2	1	1
CR2	3	5	4	3	5	3	4	3	3	5	3	5	4
CR3	4	4	5	4	4	4	5	5	4	4	4	4	5
CR4	2	1	1	1	2	2	2	2	1	2	1	2	2
CR5	5	3	3	5	3	5	3	4	5	3	5	3	3
	P27	P28	P29	P30	P31	P32	P33	P34	P35				
CR1	2	2	3	1	3	1	3	2	2				
CR2	3	4	4	4	4	5	5	5	1				
CR3	4	5	5	5	5	4	4	4	5				
CR4	1	1	1	3	1	3	1	1	3				
CR5	5	3	2	2	2	2	2	3	4				

3- Data Collected for Ratio Method

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13
CR1	100	90	60	50	50	30	40	50	70	90	70	70	70
CR2	70	30	10	30	30	10	10	30	30	30	30	40	40
CR3	50	50	30	10	10	90	70	10	10	10	10	10	30
CR4	30	10	70	90	80	50	90	90	90	80	80	60	60
CR5	10	60	90	70	60	70	60	70	50	60	90	50	10
	P14	P15	P16	P17	P18	P19	P20	P21	P22	P23	P24	P25	P26
CR1	80	70	60	70	70	70	80	70	50	90	60	70	90
CR2	50	10	30	50	10	30	20	40	40	10	40	10	20
CR3	40	40	10	30	20	20	10	10	30	30	20	30	10
CR4	60	80	80	80	60	50	60	60	70	70	80	60	70
CR5	10	50	50	10	40	10	40	30	10	50	10	50	40
	P27	P28	P29	P30	P31	P32	P33	P34	P35				
CR1	60	60	60	90	60	70	50	60	70				
CR2	40	30	30	40	30	10	10	10	80				
CR3	30	10	10	10	10	20	20	20	10				
CR4	80	70	80	70	90	50	90	80	60				
CR5	10	40	70	80	70	60	60	40	30				

4- Data Collected for Point Allocation Method

Post Graduate Students Data for Point Allocation Method													
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13
CR1	35	40	20	20	20	20	10	20	25	35	20	35	40
CR2	25	15	10	15	15	5	10	10	10	15	15	15	20
CR3	20	15	15	15	5	35	25	5	5	5	5	5	10
CR4	15	10	25	30	35	15	35	40	40	25	25	25	25
CR5	5	20	30	20	25	25	20	25	20	20	35	20	5
	P14	P15	P16	P17	P18	P19	P20	P21	P22	P23	P24	P25	P26
CR1	40	25	25	25	45	35	40	45	25	40	30	35	40
CR2	20	5	15	20	5	15	15	15	20	5	15	5	10
CR3	10	10	5	15	10	15	5	5	15	10	10	10	5
CR4	25	40	35	35	25	25	20	25	35	30	40	30	25
CR5	5	20	20	5	15	10	20	10	5	15	5	20	20
	P27	P28	P29	P30	P31	P32	P33	P34	P35	P36	P37	P38	
CR1	30	25	30	45	20	35	20	30	25				
CR2	15	15	10	10	15	5	5	5	30				
CR3	10	10	5	5	5	15	10	10	10				
CR4	35	30	40	15	35	20	40	35	20				
CR5	10	20	15	25	25	25	25	20	15				

5- Data Collected for Pairwise Comparisons and Graphical Methods

Post Graduate Students Data for Pairwise Comparisons Method									
P1					P2				
1	3	4	5	7	1	4	2	5	6
0.33	1	2	3	7	0.25	1	0.5	2	3
0.25	0.5	1	3	5	0.5	2	1	4	5
0.2	0.33	0.33	1	2	0.2	0.5	0.25	1	2
0.14	0.14	0.2	0.5	1	0.17	0.33	0.2	0.5	1
P3					P4				
1	4	2	0.5	0.25	1	2	4	0.5	0.2
0.25	1	0.5	0.2	0.14	0.5	1	3	0.3	0.2
0.5	2	1	0.33	0.2	0.25	0.33	1	0.25	0.12
2	5	3	1	0.5	2	3	4	1	0.33
4	7	5	2	1	5	5	8	3	1
P5					P6				
1	3	4	0.2	0.14	1	2	0.2	0.5	0.25
0.33	1	3	0.17	0.2	0.5	1	0.12	0.33	0.2
0.25	0.33	1	0.14	0.2	5	8	1	4	2
5	6	7	1	3	2	3	0.25	1	0.33
7	5	5	0.33	1	4	5	0.5	3	1
P7					P8				
1	3	0.33	0.2	0.5	1	2	4	0.25	0.5
0.33	1	0.17	0.12	0.2	0.5	1	2	0.2	0.33
3	6	1	0.5	2	0.25	0.5	1	0.14	0.17
5	8	2	1	3	4	5	7	1	2
2	5	0.5	0.33	1	2	3	6	0.5	1
P9					P10				
1	4	6	0.5	2	1	6	8	2	3
0.25	1	2	0.17	0.5	0.17	1	2	0.2	0.33
0.17	0.5	1	0.12	0.25	0.12	0.5	1	0.14	0.2
2	6	8	1	4	0.5	5	7	1	2
0.5	2	4	0.25	1	0.33	3	5	0.5	1
P11					P12				
1	4	6	0.5	0.33	1	3	6	2	2
0.25	1	2	0.2	0.17	0.33	1	3	0.5	0.5
0.17	0.5	1	0.14	0.11	0.17	0.33	1	0.2	0.25
2	5	7	1	0.5	0.5	2	5	1	2
3	6	9	2	1	0.5	2	4	0.5	1
P13					P14				
1	3	4	2	6	1	3	4	2	7
0.33	1	2	0.5	3	0.33	1	2	0.5	4
0.25	0.5	1	0.33	2	0.25	0.5	1	0.5	3
0.5	2	3	1	5	0.5	2	2	1	5
0.17	0.33	0.5	0.2	1	0.14	0.25	0.33	0.2	1
P15					P16				
1	6	3	0.5	2	1	3	5	0.5	2
0.17	1	0.33	0.14	0.25	0.33	1	2	0.2	0.5

0.33	3	1	0.25	0.5	0.2	0.5	1	0.14	0.25
2	7	4	1	3	2	5	7	1	3
0.5	4	2	0.33	1	0.5	2	4	0.33	1
P17					P18				
1	2	4	0.5	6	1	6	5	2	3
0.5	1	2	0.33	4	0.17	1	0.5	0.2	0.33
0.25	0.5	1	0.2	2	0.2	2	1	0.25	0.5
2	3	5	1	7	0.5	5	4	1	2
0.17	0.25	0.5	0.14	1	0.33	3	2	0.5	1
P19					P20				
1	4	5	2	6	1	6	7	2	4
0.25	1	2	0.5	2	0.17	1	2	0.25	0.5
0.2	0.5	1	0.33	2	0.14	0.5	1	0.2	0.33
0.5	2	3	1	4	0.5	4	5	1	2
0.17	0.5	0.5	0.25	1	0.25	2	3	0.5	1
P21					P22				
1	3	6	2	4	1	2	2	0.5	4
0.33	1	3	0.5	2	0.5	1	2	0.33	3
0.17	0.33	1	0.2	0.5	0.5	0.5	1	0.25	2
0.5	2	5	1	3	2	3	4	1	6
0.25	0.5	2	0.33	1	0.25	0.33	0.5	0.17	1
P23					P24				
1	8	6	2	4	1	2	4	0.5	5
0.12	1	0.5	0.17	0.25	0.5	1	2	0.25	3
0.17	2	1	0.25	0.5	0.25	0.5	1	0.17	2
0.5	6	4	1	2	2	4	6	1	7
0.25	4	2	0.5	1	0.2	0.33	0.5	0.14	1
P25					P26				
1	6	4	2	2	1	7	8	2	5
0.17	1	0.5	0.2	0.5	0.14	1	2	0.2	0.5
0.25	2	1	0.33	0.5	0.12	0.5	1	0.17	0.33
0.5	5	3	1	2	0.5	5	6	1	3
0.5	2	2	0.5	1	0.2	2	3	0.33	1
P27					P28				
1	2	3	0.5	5	1	3	5	0.5	2
0.5	1	2	0.25	3	0.33	1	2	0.25	0.5
0.33	0.5	1	0.2	2	0.2	0.5	1	0.17	0.33
2	4	5	1	7	2	4	6	1	3
0.2	0.33	0.5	0.14	1	0.5	2	3	0.33	1
P29					P30				
1	3	5	0.5	0.5	1	5	8	2	2
0.33	1	2	0.2	0.25	0.2	1	3	0.33	0.25
0.2	0.5	1	0.14	0.17	0.12	0.33	1	0.17	0.14
2	5	7	1	2	0.5	3	6	1	0.5
2	4	6	0.5	1	0.5	4	7	2	1
P31					P32				
1	3	5	0.33	0.5	1	6	5	2	2

0.33	1	2	0.17	0.25	0.17	1	0.5	0.25	0.2
0.2	0.5	1	0.12	0.17	0.2	2	1	0.33	0.25
3	6	8	1	2	0.5	4	3	1	0.5
2	4	6	0.5	1	0.5	5	4	2	1
P33					P34				
1	4	3	0.25	0.5	1	5	4	0.5	2
0.25	1	0.5	0.12	0.2	0.2	1	0.5	0.14	0.33
0.33	2	1	0.14	0.25	0.25	2	1	0.17	0.5
4	8	7	1	3	2	7	6	1	4
2	5	4	0.33	1	0.5	3	2	0.25	1
P35									
1	0.5	6	2	4					
2	1	7	0.5	5					
0.17	0.14	1	0.2	0.5					
0.5	2	5	1	3					
0.25	0.2	2	0.33	1					



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6- Data Collected for TOPSIS Method

Post Graduate Students Data for TOPSIS Method										
P1						P2				
CR1	CR2	CR3	CR4	CR5		CR1	CR2	CR3	CR4	CR5
100	80	90	90	90	A1	30	40	50	90	40
90	90	80	80	80	A2	60	50	60	10	50
100	100	100	100	100	A3	50	70	30	40	70
80	70	90	90	80	A4	30	70	30	90	20
70	60	90	70	70	A5	40	30	40	50	60
P3						P4				
70	60	90	60	60	A1	80	70	80	50	80
60	50	60	70	70	A2	60	60	70	40	70
100	70	80	70	50	A3	70	90	100	70	60
40	30	50	40	40	A4	50	50	60	30	50
30	20	30	30	30	A5	40	40	40	20	40
P5						P6				
70	80	50	80	70	A1	80	70	70	70	60
60	70	80	70	50	A2	70	60	60	60	50
100	90	90	100	80	A3	100	90	90	90	90
50	40	60	60	40	A4	30	30	30	30	30
30	30	70	40	30	A5	20	20	20	20	20
P7						P8				
90	70	70	60	60	A1	80	70	70	70	60
70	60	40	40	30	A2	70	50	50	40	40
100	90	90	80	70	A3	100	80	90	80	80
40	40	30	20	20	A4	40	20	30	30	20
30	30	20	10	10	A5	20	10	20	20	10
P9						P10				
80	80	70	90	100	A1	70	60	80	60	60
50	60	50	50	60	A2	60	50	70	50	50
100	70	60	70	80	A3	90	80	100	90	90
20	30	30	30	30	A4	30	30	40	30	20
10	20	20	20	20	A5	20	10	30	10	10
P11						P12				
70	60	90	70	80	A1	80	70	60	80	80
80	80	60	80	70	A2	60	50	80	60	60
90	90	80	90	100	A3	70	80	100	70	70

30	50	30	60	60	A4	40	40	40	20	40
20	30	20	50	50	A5	30	30	30	10	20
P13						P14				
80	80	80	70	70	A1	90	70	90	90	70
60	60	50	80	60	A2	60	80	60	60	60
100	70	90	100	90	A3	70	100	80	80	100
40	40	40	50	40	A4	40	40	30	50	30
30	30	30	40	30	A5	30	30	20	30	20
P15						P16				
70	70	70	80	80	A1	70	70	80	90	70
80	50	60	60	70	A2	60	60	70	70	60
60	60	90	70	100	A3	90	80	90	100	90
40	30	40	40	40	A4	40	40	40	60	40
30	20	30	30	30	A5	30	30	30	50	30
P17						P18				
90	80	80	70	80	A1	60	70	70	80	90
70	60	50	80	60	A2	50	80	80	90	80
80	70	60	50	100	A3	70	60	60	60	70
60	50	40	40	40	A4	30	40	40	50	30
50	40	30	30	30	A5	20	30	30	30	20
P19						P20				
70	70	80	80	80	A1	70	60	50	90	80
80	80	60	70	60	A2	60	50	40	80	60
90	90	70	90	100	A3	80	70	60	100	100
60	60	50	50	40	A4	50	40	30	70	40
50	50	40	40	30	A5	40	30	20	60	20
P21						P22				
80	80	60	80	60	A1	70	50	70	60	70
90	90	50	60	50	A2	80	80	50	70	50
60	70	70	100	80	A3	90	70	90	80	100
50	50	40	40	30	A4	60	40	40	50	40
30	40	30	30	20	A5	50	30	30	40	30
P23						P24				
80	80	50	60	80	A1	70	60	60	90	70
60	70	60	70	60	A2	60	50	40	80	50
90	100	80	80	100	A3	90	80	80	100	100
50	60	40	50	40	A4	40	40	20	50	30
40	50	30	40	20	A5	30	30	10	40	10
P25						P26				
70	80	70	80	70	A1	70	80	60	70	70

80	60	60	60	50	A2	60	70	70	80	60
90	90	90	70	100	A3	90	100	90	90	100
50	40	30	40	30	A4	40	60	40	50	40
40	30	20	30	20	A5	30	40	50	60	30
P27						P28				
80	80	80	60	60	A1	80	80	80	70	70
60	70	70	70	80	A2	90	60	70	60	60
70	90	60	90	100	A3	70	70	90	80	100
40	60	50	50	40	A4	60	40	40	50	40
30	50	40	40	30	A5	50	30	30	30	30
P29						P30				
70	70	70	90	80	A1	80	70	60	80	60
60	80	60	60	60	A2	60	50	50	90	50
80	100	80	80	100	A3	70	80	80	70	100
50	50	50	40	40	A4	50	40	40	50	30
40	40	40	30	30	A5	40	30	30	40	20
P31						P32				
60	90	90	80	80	A1	90	90	90	70	70
50	60	60	60	70	A2	70	70	60	50	80
80	70	80	100	90	A3	80	80	80	100	100
30	30	40	40	50	A4	50	50	40	30	50
20	20	30	30	40	A5	40	30	30	20	40
P33						P34				
90	90	80	90	70	A1	70	70	70	80	90
70	70	70	70	50	A2	60	60	60	60	70
80	80	90	100	90	A3	90	80	90	100	80
50	50	50	50	40	A4	40	50	30	40	50
40	40	40	40	30	A5	30	40	20	30	40
P35										
70	70	60	90	90	A1					
80	60	70	80	70	A2					
90	90	90	100	80	A3					
50	50	50	50	50	A4					
40	40	30	40	40	A5					

Appendix E

Inconsistency Matrices and Processing by TROI Method

1- Inconsistency Ratios in the Matrices Judgements

Inconsistency Ratio from Administrative Group Matrices									
P3 CR= 0.167					P5 CR= 0.103				
1	2	0.33	0.25	3	1	4	3	0.33	0.2
0.5	1	0.2	0.33	6	0.25	1	0.5	0.2	0.14
3	5	1	0.33	5	0.33	2	1	0.25	0.17
4	3	3	1	3	3	5	4	1	3
0.33	0.17	0.2	0.33	1	5	7	6	0.33	1
P7 CR= 0.111					P14 CR=0.58				
1	0.33	2	0.2	0.5	1	0.33	0.25	0.5	2
3	1	5	2	0.5	3	1	0.33	3	0.2
0.5	0.2	1	0.14	0.25	4	3	1	0.33	0.14
5	0.5	7	1	3	2	0.33	3	1	0.25
2	2	4	0.33	1	0.5	5	7	4	1
P17 CR= 0.61					P18 CR= 0.51				
1	3	5	0.2	0.33	1	3	5	0.33	2
0.33	1	2	0.17	0.25	0.33	1	3	2	3
0.2	0.5	1	0.12	3	0.2	0.33	1	5	7
5	6	8	1	0.33	3	0.5	0.2	1	3
3	4	0.33	3	1	0.5	0.33	0.14	0.33	1

Inconsistency Ratio from Academic Staff.									
P4 CR= 0.423					P7 CR= 0.15				
1	2	0.5	0.33	3	1	0.33	0.5	2	0.33
0.5	1	0.33	0.2	2	3	1	2	5	7
2	3	1	0.5	0.17	2	0.5	1	4	5
3	5	2	1	8	0.5	0.2	0.25	1	2
0.33	0.5	6	0.12	1	3	0.14	0.2	0.5	1
P15 CR= 0.273					P24 CR=0.27				
1	7	5	2	3	1	2	3	0.14	2
0.14	1	2	3	0.25	0.5	1	3	0.25	0.33
0.2	0.5	1	0.33	0.33	0.33	0.33	1	0.14	0.2
0.5	0.33	3	1	3	7	4	7	1	0.33
0.33	4	3	0.33	1	0.5	3	5	3	1
P27 CR= 0.18									
1	4	6	0.5	3					
0.25	1	3	0.2	0.5					
0.17	0.33	1	0.14	0.25					
2	5	7	1	0.33					
0.33	2	4	3	1					
Inconsistency Ratio from Post Graduate Students									
P5 CR= 0.123					Universiti Utara Malaysia				
1	3	4	0.2	0.14					
0.33	1	3	0.17	0.2					
0.25	0.33	1	0.14	0.2					
5	6	7	1	3					
7	5	5	0.33	1					

2- Processing the Inconsistency Matrices by TROI Method

Administrative group									
P3 CR= 0.017					P5 CR= 0.036				
1	2	0.33	0.25	3	1	4	3	0.33	0.2
0.5	1	0.2	0.17	2	0.25	1	0.5	0.14	0.11
3	5	1	0.5	6	0.33	2	1	0.17	0.125
4	6	2	1	7	3	7	6	1	0.33
0.33	0.5	0.17	0.14	1	5	9	8	3	1
P7 CR= 0.022					P14 CR=0.014				
1	0.33	2	0.2	0.5	1	0.33	0.25	0.5	2
3	1	5	0.33	2	3	1	0.5	2	5
0.5	0.2	1	0.14	0.25	4	2	1	3	6
5	3	7	1	4	2	0.5	0.33	1	4
2	0.5	4	0.25	1	0.5	0.2	0.17	0.25	1
P17 CR= 0.025					P18 CR= 0.029				
1	3	4	0.25	0.33	1	3	5	0.33	2
0.33	1	2	0.14	0.17	0.33	1	3	0.17	0.5
0.25	0.5	1	0.125	0.14	0.2	0.33	1	0.125	0.25
4	7	8	1	2	3	6	8	1	5
3	6	7	0.5	1	0.5	2	4	0.2	1

Academic Staff Group									
P4 CR= 0.012					P7 CR= 0.06				
1	2	0.5	0.33	3	1	0.33	0.5	2	0.33
0.5	1	0.25	0.2	2	3	1	2	5	1
2	4	1	0.5	5	2	0.5	1	4	0.5
3	5	2	1	6	0.5	0.2	0.25	1	0.2
0.33	0.5	0.2	0.17	1	3	1	2	5	1
P15 CR= 0.03					P24 CR=0.059				
1	7	5	2	3	1	2	2	0.17	2
0.14	1	0.33	0.17	0.2	0.5	1	1	0.125	0.25
0.2	3	1	0.25	0.33	0.5	1	1	0.125	1
0.5	6	4	1	2	6	8	8	1	8
0.33	5	3	0.5	1	0.5	4	1	0.125	1
P27 CR= 0.03									
1	4	6	0.5	3					
0.25	1	3	0.17	0.5					
0.17	0.33	1	0.125	0.25					
2	6	8	1	5					
0.33	2	4	0.2	1					

Post Graduate Students Group				
P5 CR= 0.033				
1	3	2	0.2	0.2
0.33	1	2	0.125	0.125
0.5	0.5	1	0.14	0.14
5	8	7	1	1
5	8	7	1	1

Appendix F

Final Weights from Each Method for Each Group

1- Rating Method

I. Administrative Group

Participants	CR1	CR2	CR3	CR4	CR5

P 1	0.2632	0.1053	0.1842	0.2105	0.2368
P 2	0.1250	0.2188	0.2500	0.3125	0.0938
P 3	0.1471	0.2353	0.2941	0.2059	0.1176
P 4	0.2188	0.0938	0.1250	0.2500	0.3125
P 5	0.1935	0.0968	0.1290	0.2581	0.3226
P 6	0.3226	0.1290	0.0968	0.1935	0.2581
P 7	0.1563	0.2188	0.1250	0.3125	0.1875
P 8	0.1212	0.1515	0.1818	0.2424	0.3030
P 9	0.2500	0.1250	0.0938	0.3125	0.2188
P10	0.2250	0.2000	0.2500	0.1750	0.1500
P11	0.1750	0.2500	0.2250	0.2000	0.1500
P12	0.3125	0.0938	0.1563	0.1875	0.2500
P13	0.1935	0.1290	0.0968	0.3226	0.2581
P14	0.2424	0.1515	0.0909	0.2121	0.3030
P15	0.2857	0.1714	0.1143	0.2000	0.2286
P16	0.2059	0.1471	0.0882	0.2647	0.2941
P17	0.1935	0.1613	0.0645	0.3226	0.2581
P18	0.2414	0.1379	0.0690	0.3448	0.2069
P19	0.1471	0.0882	0.2059	0.2941	0.2647
P20	0.2500	0.1563	0.1875	0.3125	0.0938
P21	0.3030	0.1515	0.2121	0.2424	0.0909
P22	0.2500	0.0833	0.1667	0.2778	0.2222

Geometric Mean	0.2111	0.1423	0.1417	0.2516	0.2043
Normalized Weights	0.2220	0.1496	0.1490	0.2646	0.2148
Rank	2	4	5	1	3

II. Academic Staff Group

Participators	CR1	CR2	CR3	CR4	CR5

P 1	0.1944	0.1667	0.1389	0.2778	0.2222
P 2	0.2778	0.1667	0.1389	0.1944	0.2222
P 3	0.2250	0.2000	0.1500	0.1750	0.2500
P 4	0.1667	0.1944	0.2778	0.2222	0.1389
P 5	0.1389	0.2222	0.2778	0.1944	0.1667
P 6	0.2250	0.2500	0.1750	0.2000	0.1500
P 7	0.2250	0.2000	0.2500	0.1500	0.1750
P 8	0.2368	0.2632	0.1579	0.1316	0.2105
P 9	0.2105	0.2368	0.1316	0.1579	0.2632
P10	0.1750	0.1500	0.2500	0.2000	0.2250
P11	0.2424	0.3030	0.2121	0.1515	0.0909
P12	0.1563	0.1875	0.2500	0.3125	0.0938
P13	0.1818	0.1515	0.3030	0.1212	0.2424
P14	0.2424	0.1818	0.1515	0.1212	0.3030
P15	0.3030	0.1212	0.1515	0.2424	0.1818
P16	0.1935	0.1290	0.2581	0.0968	0.3226
P17	0.1750	0.2250	0.2000	0.1500	0.2500
P18	0.2000	0.2250	0.2500	0.1750	0.1500
P19	0.2500	0.2250	0.2000	0.1750	0.1500
P20	0.0882	0.1471	0.2059	0.2647	0.2941
P21	0.2162	0.1622	0.2703	0.2432	0.1081
P22	0.2857	0.2286	0.2000	0.1714	0.1143
P23	0.2000	0.2500	0.2250	0.1750	0.1500
P24	0.1935	0.1290	0.0968	0.3226	0.2581
P25	0.3226	0.2581	0.1935	0.1290	0.0968
P26	0.2059	0.1765	0.0882	0.2941	0.2353
P27	0.2647	0.1471	0.0882	0.2941	0.2059
P28	0.2000	0.2500	0.2250	0.1750	0.1500
P29	0.2222	0.1944	0.1389	0.1667	0.2778
P30	0.2941	0.1471	0.0588	0.2353	0.2647
P31	0.3125	0.1250	0.0625	0.2188	0.2813
P32	0.1750	0.2000	0.2250	0.2500	0.1500
P33	0.3125	0.1563	0.2188	0.2500	0.0625
P34	0.2308	0.1795	0.1282	0.2051	0.2564
P35	0.2571	0.1714	0.0857	0.2857	0.2000
P36	0.2857	0.1143	0.1714	0.2000	0.2286
P37	0.2059	0.1471	0.1176	0.2941	0.2353
P38	0.2162	0.1081	0.2703	0.2432	0.1622

Geometric					

Mean 0.1857	0.2175	0.1807	0.1702	0.1986	
Normalized Weights 0.1950	0.2283	0.1896	0.1787	0.2084	
Rank	1	4	5	2	3

III. Postgraduate Students Group

Participators	CR1	CR2	CR3	CR4	CR5
P 1	0.2500	0.2250	0.2000	0.1750	0.1500
P 2	0.3704	0.1111	0.1852	0.0741	0.2593
P 3	0.1875	0.0938	0.1250	0.2813	0.3125
P 4	0.1935	0.1290	0.0968	0.3226	0.2581
P 5	0.1724	0.1379	0.1034	0.3448	0.2414
P 6	0.1875	0.0938	0.3125	0.1563	0.2500
P 7	0.1471	0.0882	0.2647	0.2941	0.2059
P 8	0.1944	0.1667	0.1111	0.2778	0.2500
P 9	0.2500	0.1667	0.0833	0.2778	0.2222
P10	0.2941	0.1471	0.0882	0.2647	0.2059
P11	0.2353	0.1471	0.0588	0.2647	0.2941
P12	0.2778	0.1667	0.1111	0.2500	0.1944
P13	0.2778	0.1944	0.1667	0.2222	0.1389
P14	0.3448	0.1724	0.1379	0.2414	0.1034
P15	0.2286	0.1143	0.1714	0.2857	0.2000
P16	0.2500	0.1667	0.1111	0.2778	0.1944
P17	0.2258	0.1935	0.1613	0.3226	0.0968
P18	0.3226	0.0968	0.1613	0.2258	0.1935
P19	0.2564	0.2051	0.1795	0.2308	0.1282
P20	0.3333	0.1333	0.1000	0.2333	0.2000
P21	0.3030	0.2121	0.0909	0.2424	0.1515
P22	0.2500	0.1875	0.1563	0.3125	0.0938
P23	0.3226	0.0968	0.1613	0.2258	0.1935
P24	0.2333	0.2000	0.1333	0.3333	0.1000
P25	0.2778	0.1111	0.1667	0.2500	0.1944
P26	0.3226	0.1290	0.0645	0.2581	0.2258
P27	0.2727	0.2121	0.1515	0.3030	0.0606
P28	0.2500	0.1429	0.0714	0.3571	0.1786
P29	0.2162	0.1622	0.1081	0.2703	0.2432

P30	0.2778	0.1667	0.0833	0.2222	0.2500
P31	0.2059	0.1471	0.1176	0.2941	0.2353
P32	0.2857	0.1143	0.1714	0.2000	0.2286
P33	0.2069	0.0690	0.1379	0.3448	0.2414
P34	0.2500	0.0625	0.1563	0.3125	0.2188
P35	0.2308	0.2564	0.1282	0.2051	0.1795

Geometric Mean	0.2491	0.1415	0.1290	0.2531	0.1861
Normalized Weights	0.2598	0.1476	0.1346	0.2640	0.1941
Rank	2	4	5	1	3

2- Ratio Method

I- Administrative Group

Participators	CR1	CR2	CR3	CR4	CR5

P 1	0.3200	0.0400	0.1200	0.2400	0.2800
P 2	0.1364	0.2273	0.2727	0.3182	0.0455
P 3	0.1154	0.2692	0.2308	0.3462	0.0385
P 4	0.2174	0.0435	0.1304	0.2609	0.3478
P 5	0.2000	0.0400	0.1200	0.2800	0.3600
P 6	0.2609	0.1304	0.0435	0.2174	0.3478
P 7	0.1667	0.2500	0.0417	0.3333	0.2083
P 8	0.0500	0.1500	0.2000	0.2500	0.3500
P 9	0.3077	0.0769	0.0385	0.3462	0.2308
P10	0.2800	0.2000	0.3600	0.1200	0.0400
P11	0.1154	0.3846	0.2692	0.1923	0.0385
P12	0.3600	0.0400	0.1200	0.2000	0.2800
P13	0.2222	0.1481	0.0370	0.2593	0.3333
P14	0.2593	0.1481	0.0370	0.2222	0.3333
P15	0.3333	0.1481	0.0370	0.2222	0.2593
P16	0.2000	0.1200	0.0400	0.2800	0.3600
P17	0.2000	0.1200	0.0400	0.3600	0.2800
P18	0.2609	0.1304	0.0435	0.3478	0.2174
P19	0.1600	0.0400	0.2000	0.3200	0.2800
P20	0.3043	0.1304	0.1739	0.3478	0.0435
P21	0.3750	0.1250	0.1667	0.2917	0.0417
P22	0.2609	0.0435	0.1304	0.3478	0.2174

Geometric Mean	0.2127	0.1102	0.0970	0.2689	0.1693
Normalized weights	0.2478	0.1285	0.1130	0.3134	0.1973
Rank	2	4	5	1	3

II- Academic Staff Group

Participators	CR1	CR2	CR3	CR4	CR5

P 1	0.3214	0.1429	0.0357	0.2143	0.2857
P 2	0.3810	0.0952	0.0476	0.1429	0.3333
P 3	0.2963	0.1852	0.0370	0.1481	0.3333
P 4	0.1364	0.2273	0.3182	0.2727	0.0455
P 5	0.0357	0.2857	0.3571	0.1786	0.1429
P 6	0.3214	0.3571	0.1071	0.1786	0.0357
P 7	0.2692	0.2308	0.3077	0.0385	0.1538
P 8	0.3043	0.3478	0.0870	0.0435	0.2174
P 9	0.2500	0.2857	0.0357	0.1071	0.3214
P10	0.1333	0.0333	0.3333	0.2333	0.2667
P11	0.2609	0.3478	0.2174	0.1304	0.0435
P12	0.1304	0.2174	0.2609	0.3478	0.0435
P13	0.2174	0.1304	0.3478	0.0435	0.2609
P14	0.2609	0.2174	0.0435	0.1304	0.3478
P15	0.3333	0.0417	0.1667	0.2500	0.2083
P16	0.2500	0.0833	0.2917	0.0417	0.3333
P17	0.1429	0.2500	0.2143	0.0357	0.3571
P18	0.2083	0.2917	0.3333	0.1250	0.0417
P19	0.3478	0.2609	0.2174	0.1304	0.0435
P20	0.0435	0.1304	0.2174	0.2609	0.3478
P21	0.2143	0.1429	0.3571	0.2500	0.0357
P22	0.3333	0.2963	0.2222	0.1111	0.0370
P23	0.2333	0.3000	0.2667	0.1667	0.0333
P24	0.2000	0.1200	0.0400	0.3600	0.2800
P25	0.3600	0.2800	0.2000	0.1200	0.0400
P26	0.2174	0.1304	0.0435	0.3478	0.2609
P27	0.2800	0.1600	0.0400	0.3200	0.2000
P28	0.2000	0.3600	0.2800	0.1200	0.0400
P29	0.2609	0.2174	0.0435	0.1739	0.3043
P30	0.3200	0.1200	0.0400	0.2400	0.2800
P31	0.3462	0.1538	0.0385	0.1923	0.2692

P32	0.1481	0.2222	0.2593	0.3333	0.0370
P33	0.3333	0.1250	0.2083	0.2917	0.0417
P34	0.2800	0.1200	0.0400	0.2000	0.3600
P35	0.2593	0.1481	0.0370	0.3333	0.2222
P36	0.3077	0.0385	0.1538	0.2308	0.2692
P37	0.2308	0.1538	0.0385	0.3077	0.2692
P38	0.2381	0.0476	0.3333	0.2857	0.0952

Geometric Mean	0.2260	0.1641	0.1234	0.1651	0.1359
Normalized weights	0.2775	0.2014	0.1516	0.2027	0.1668
Rank	1	3	5	2	4

III- Postgraduate Students Group

Participators	CR1	CR2	CR3	CR4	CR5

P 1	0.3846	0.2692	0.1923	0.1154	0.0385
P 2	0.3750	0.1250	0.2083	0.0417	0.2500
P 3	0.2308	0.0385	0.1154	0.2692	0.3462
P 4	0.2000	0.1200	0.0400	0.3600	0.2800
P 5	0.2174	0.1304	0.0435	0.3478	0.2609
P 6	0.1200	0.0400	0.3600	0.2000	0.2800
P 7	0.1481	0.0370	0.2593	0.3333	0.2222
P 8	0.2000	0.1200	0.0400	0.3600	0.2800
P 9	0.2800	0.1200	0.0400	0.3600	0.2000
P10	0.3333	0.1111	0.0370	0.2963	0.2222
P11	0.2500	0.1071	0.0357	0.2857	0.3214
P12	0.3043	0.1739	0.0435	0.2609	0.2174
P13	0.3333	0.1905	0.1429	0.2857	0.0476
P14	0.3333	0.2083	0.1667	0.2500	0.0417
P15	0.2800	0.0400	0.1600	0.3200	0.2000
P16	0.2609	0.1304	0.0435	0.3478	0.2174
P17	0.2917	0.2083	0.1250	0.3333	0.0417
P18	0.3500	0.0500	0.1000	0.3000	0.2000
P19	0.3889	0.1667	0.1111	0.2778	0.0556
P20	0.3810	0.0952	0.0476	0.2857	0.1905
P21	0.3333	0.1905	0.0476	0.2857	0.1429
P22	0.2500	0.2000	0.1500	0.3500	0.0500
P23	0.3600	0.0400	0.1200	0.2800	0.2000
P24	0.2857	0.1905	0.0952	0.3810	0.0476

P25	0.3182	0.0455	0.1364	0.2727	0.2273
P26	0.3913	0.0870	0.0435	0.3043	0.1739
P27	0.2727	0.1818	0.1364	0.3636	0.0455
P28	0.2857	0.1429	0.0476	0.3333	0.1905
P29	0.2400	0.1200	0.0400	0.3200	0.2800
P30	0.3103	0.1379	0.0345	0.2414	0.2759
P31	0.2308	0.1154	0.0385	0.3462	0.2692
P32	0.3333	0.0476	0.0952	0.2381	0.2857
P33	0.2174	0.0435	0.0870	0.3913	0.2609
P34	0.2857	0.0476	0.0952	0.3810	0.1905
P35	0.2800	0.3200	0.0400	0.2400	0.1200

Geometric Mean	0.2785	0.1050	0.0800	0.2805	0.1576
Normalized weights	0.3089	0.1164	0.0887	0.3111	0.1748
Rank	2	4	5	1	3

3- Point Allocation Method

I- Administrative Group

Participants	CR1	CR2	CR3	CR4	CR5

P 1	0.3000	0.1000	0.1500	0.2000	0.2500
P 2	0.1000	0.2000	0.3000	0.3500	0.0500
P 3	0.1000	0.2500	0.3500	0.2500	0.0500
P 4	0.2000	0.1000	0.1500	0.2000	0.3500
P 5	0.2000	0.0500	0.1000	0.2500	0.4000
P 6	0.3500	0.1000	0.0500	0.2000	0.3000
P 7	0.1500	0.2500	0.1000	0.3000	0.2000
P 8	0.1000	0.1500	0.2000	0.2500	0.3000
P 9	0.1500	0.2500	0.1000	0.3000	0.2000
P10	0.2500	0.1500	0.4500	0.1000	0.0500
P11	0.1500	0.3500	0.2500	0.2000	0.0500
P12	0.3500	0.0500	0.1000	0.2000	0.3000
P13	0.2000	0.1500	0.0500	0.3500	0.2500
P14	0.2500	0.1000	0.0500	0.2000	0.4000
P15	0.4000	0.1000	0.0500	0.2000	0.2500
P16	0.2000	0.1500	0.0500	0.2500	0.3500
P17	0.2000	0.1500	0.0500	0.3500	0.2500

P18	0.2500	0.1500	0.0500	0.3500	0.2000
P19	0.1500	0.0500	0.2000	0.3500	0.2500
P20	0.3000	0.1000	0.2000	0.3500	0.0500
P21	0.3000	0.1500	0.2000	0.2500	0.1000
P22	0.3000	0.0500	0.1000	0.4000	0.1500

Geometric Mean	0.2081	0.1242	0.1173	0.2543	0.1739
Normalized weights	0.2371	0.1415	0.1336	0.2897	0.1981
Rank	2	4	5	1	3

II- Academic Staff Group

Participators	CR1	CR2	CR3	CR4	CR5

P 1	0.2500	0.1000	0.0500	0.3500	0.2500
P 2	0.4500	0.0500	0.0500	0.2000	0.2500
P 3	0.3000	0.2000	0.0500	0.1000	0.3500
P 4	0.1500	0.2000	0.3000	0.2500	0.1000
P 5	0.1000	0.2500	0.4000	0.1500	0.1000
P 6	0.2500	0.3000	0.1500	0.2000	0.1000
P 7	0.2500	0.2000	0.3000	0.1000	0.1500
P 8	0.3000	0.3500	0.1000	0.0500	0.2000
P 9	0.2000	0.2500	0.0500	0.1000	0.4000
P10	0.1500	0.0500	0.3000	0.2000	0.3000
P11	0.3000	0.4000	0.1500	0.1000	0.0500
P12	0.1500	0.2000	0.2500	0.3500	0.0500
P13	0.2000	0.1500	0.3000	0.1000	0.2500
P14	0.2500	0.2000	0.1000	0.1500	0.3000
P15	0.4000	0.1000	0.1000	0.2500	0.1500
P16	0.2500	0.0500	0.3000	0.0500	0.3500
P17	0.1000	0.1500	0.2000	0.2500	0.3000
P18	0.1500	0.2500	0.4000	0.1000	0.1000
P19	0.4500	0.2500	0.1500	0.1000	0.0500
P20	0.0500	0.1500	0.2000	0.2500	0.3500
P21	0.2000	0.1500	0.3500	0.2500	0.0500
P22	0.3500	0.2500	0.2000	0.1500	0.0500
P23	0.2000	0.4000	0.2500	0.1000	0.0500
P24	0.2000	0.1500	0.0500	0.3500	0.2500
P25	0.3500	0.3000	0.2000	0.1000	0.0500
P26	0.2000	0.1000	0.0500	0.3500	0.3000

P27	0.2000	0.1500	0.1000	0.4000	0.1500
P28	0.2000	0.3500	0.2500	0.1500	0.0500
P29	0.3000	0.2000	0.0500	0.1000	0.3500
P30	0.3500	0.1500	0.0500	0.2000	0.2500
P31	0.3500	0.1500	0.0500	0.2000	0.2500
P32	0.1500	0.2000	0.2000	0.4000	0.0500
P33	0.4000	0.1000	0.1500	0.3000	0.0500
P34	0.3000	0.1000	0.0500	0.2000	0.3500
P35	0.3000	0.1000	0.0500	0.3500	0.2000
P36	0.4500	0.0500	0.1000	0.1500	0.2500
P37	0.2000	0.1000	0.0500	0.3500	0.3000
P38	0.2000	0.1000	0.3000	0.2500	0.1500

Geometric Mean	0.2305	0.1580	0.1306	0.1769	0.1509
Normalized weights	0.2722	0.1865	0.1542	0.2089	0.1782
Rank	1	3	5	2	4

III- Postgraduate Students Group

Participants	CR1	CR2	CR3	CR4	CR5

P 1	0.3500	0.2500	0.2000	0.1500	0.0500
P 2	0.4000	0.1500	0.1500	0.1000	0.2000
P 3	0.2000	0.1000	0.1500	0.2500	0.3000
P 4	0.2000	0.1500	0.1500	0.3000	0.2000
P 5	0.2000	0.1500	0.0500	0.3500	0.2500
P 6	0.2000	0.0500	0.3500	0.1500	0.2500
P 7	0.1000	0.1000	0.2500	0.3500	0.2000
P 8	0.2000	0.1000	0.0500	0.4000	0.2500
P 9	0.2500	0.1000	0.0500	0.4000	0.2000
P10	0.3500	0.1500	0.0500	0.2500	0.2000
P11	0.2000	0.1500	0.0500	0.2500	0.3500
P12	0.3500	0.1500	0.0500	0.2500	0.2000
P13	0.4000	0.2000	0.1000	0.2500	0.0500
P14	0.4000	0.2000	0.1000	0.2500	0.0500
P15	0.2500	0.0500	0.1000	0.4000	0.2000
P16	0.2500	0.1500	0.0500	0.3500	0.2000
P17	0.2500	0.2000	0.1500	0.3500	0.0500
P18	0.4500	0.0500	0.1000	0.2500	0.1500
P19	0.3500	0.1500	0.1500	0.2500	0.1000

P20	0.4000	0.1500	0.0500	0.2000	0.2000
P21	0.4500	0.1500	0.0500	0.2500	0.1000
P22	0.2500	0.2000	0.1500	0.3500	0.0500
P23	0.4000	0.0500	0.1000	0.3000	0.1500
P24	0.3000	0.1500	0.1000	0.4000	0.0500
P25	0.3500	0.0500	0.1000	0.3000	0.2000
P26	0.4000	0.1000	0.0500	0.2500	0.2000
P27	0.3000	0.1500	0.1000	0.3500	0.1000
P28	0.2500	0.1500	0.1000	0.3000	0.2000
P29	0.3000	0.1000	0.0500	0.4000	0.1500
P30	0.4500	0.1000	0.0500	0.1500	0.2500
P31	0.2000	0.1500	0.0500	0.3500	0.2500
P32	0.3500	0.0500	0.1500	0.2000	0.2500
P33	0.2000	0.0500	0.1000	0.4000	0.2500
P34	0.3000	0.0500	0.1000	0.3500	0.2000
P35	0.2500	0.3000	0.1000	0.2000	0.1500

Geometric Mean	0.2854	0.1151	0.0910	0.2733	0.1546
Normalized weights	0.3104	0.1252	0.0990	0.2973	0.1681
Rank	1	4	5	2	3

4- Rank Sum Method

I- Administrative Group

Participators	CR1	CR2	CR3	CR4	CR5

P 1	0.3333	0.0667	0.1333	0.2000	0.2667
P 2	0.1333	0.2000	0.2667	0.3333	0.0667
P 3	0.1333	0.2667	0.3333	0.2000	0.0667
P 4	0.2000	0.0667	0.1333	0.2667	0.3333
P 5	0.2000	0.0667	0.1333	0.2667	0.3333
P 6	0.3333	0.1333	0.0667	0.2000	0.2667
P 7	0.1333	0.2667	0.0667	0.3333	0.2000
P 8	0.0667	0.1333	0.2000	0.2667	0.3333
P 9	0.2667	0.1333	0.0667	0.3333	0.2000
P10	0.2667	0.2000	0.3333	0.1333	0.0667
P11	0.1333	0.3333	0.2667	0.2000	0.0667
P12	0.3333	0.0667	0.1333	0.2000	0.2667

P13	0.2000	0.1333	0.0667	0.3333	0.2667
P14	0.2667	0.1333	0.0667	0.2000	0.3333
P15	0.3333	0.1333	0.0667	0.2000	0.2667
P16	0.2000	0.1333	0.0667	0.2667	0.3333
P17	0.2000	0.1333	0.0667	0.3333	0.2667
P18	0.2667	0.1333	0.0667	0.3333	0.2000
P19	0.1333	0.0667	0.2000	0.3333	0.2667
P20	0.2667	0.1333	0.2000	0.3333	0.0667
P21	0.3333	0.1333	0.2000	0.2667	0.0667
P22	0.2667	0.0667	0.1333	0.3333	0.2000

Geometric Mean	0.2108	0.1271	0.1251	0.2583	0.1824
Normalized weights	0.2332	0.1407	0.1384	0.2858	0.2018
Rank	2	4	5	1	3

II- Academic Staff Group

Participants	CR1	CR2	CR3	CR4	CR5

P 1	0.2000	0.1333	0.0667	0.3333	0.2667
P 2	0.3333	0.1333	0.0667	0.2000	0.2667
P 3	0.2667	0.2000	0.0667	0.1333	0.3333
P 4	0.1333	0.2000	0.3333	0.2667	0.0667
P 5	0.0667	0.2667	0.3333	0.2000	0.1333
P 6	0.2667	0.3333	0.1333	0.2000	0.0667
P 7	0.2667	0.2000	0.3333	0.0667	0.1333
P 8	0.2667	0.3333	0.1333	0.0667	0.2000
P 9	0.2000	0.2667	0.0667	0.1333	0.3333
P10	0.1333	0.0667	0.3333	0.2000	0.2667
P11	0.2667	0.3333	0.2000	0.1333	0.0667
P12	0.1333	0.2000	0.2667	0.3333	0.0667
P13	0.2000	0.1333	0.3333	0.0667	0.2667
P14	0.2667	0.2000	0.0667	0.1333	0.3333
P15	0.3333	0.0667	0.1333	0.2667	0.2000
P16	0.2000	0.1333	0.2667	0.0667	0.3333
P17	0.1333	0.2667	0.2000	0.0667	0.3333
P18	0.2000	0.2667	0.3333	0.1333	0.0667
P19	0.3333	0.2667	0.2000	0.1333	0.0667
P20	0.0667	0.1333	0.2000	0.2667	0.3333
P21	0.2000	0.1333	0.3333	0.2667	0.0667

P22	0.3333	0.2667	0.2000	0.1333	0.0667
P23	0.2000	0.3333	0.2667	0.1333	0.0667
P24	0.2000	0.1333	0.0667	0.3333	0.2667
P25	0.3333	0.2667	0.2000	0.1333	0.0667
P26	0.2000	0.1333	0.0667	0.3333	0.2667
P27	0.2667	0.1333	0.0667	0.3333	0.2000
P28	0.2000	0.3333	0.2667	0.1333	0.0667
P29	0.2667	0.2000	0.0667	0.1333	0.3333
P30	0.3333	0.1333	0.0667	0.2000	0.2667
P31	0.3333	0.1333	0.0667	0.2000	0.2667
P32	0.1333	0.2000	0.2667	0.3333	0.0667
P33	0.3333	0.1333	0.2000	0.2667	0.0667
P34	0.2667	0.1333	0.0667	0.2000	0.3333
P35	0.2667	0.1333	0.0667	0.3333	0.2000
P36	0.3333	0.0667	0.1333	0.2000	0.2667
P37	0.2000	0.1333	0.0667	0.3333	0.2667
P38	0.2000	0.0667	0.3333	0.2667	0.1333

Geometric Mean	0.2179	0.1712	0.1479	0.1794	0.1598
Normalized weights	0.2487	0.1954	0.1688	0.2047	0.1824
Rank	1	3	5	2	4

III- Postgraduate Students Group

Participators	CR1	CR2	CR3	CR4	CR5

P 1	0.3333	0.2667	0.2000	0.1333	0.0667
P 2	0.3333	0.1333	0.2000	0.0667	0.2667
P 3	0.2000	0.0667	0.1333	0.2667	0.3333
P 4	0.2000	0.1333	0.0667	0.3333	0.2667
P 5	0.2000	0.1333	0.0667	0.3333	0.2667
P 6	0.2000	0.0667	0.3333	0.1333	0.2667
P 7	0.1333	0.0667	0.2667	0.3333	0.2000
P 8	0.2000	0.1333	0.0667	0.3333	0.2667
P 9	0.2667	0.1333	0.0667	0.3333	0.2000
P10	0.3333	0.1333	0.0667	0.2667	0.2000
P11	0.2000	0.1333	0.0667	0.2667	0.3333
P12	0.3333	0.1333	0.0667	0.2667	0.2000
P13	0.3333	0.2000	0.1333	0.2667	0.0667
P14	0.3333	0.2000	0.1333	0.2667	0.0667

P15	0.2667	0.0667	0.1333	0.3333	0.2000
P16	0.2667	0.1333	0.0667	0.3333	0.2000
P17	0.2667	0.2000	0.1333	0.3333	0.0667
P18	0.3333	0.0667	0.1333	0.2667	0.2000
P19	0.3333	0.2000	0.1333	0.2667	0.0667
P20	0.3333	0.1333	0.0667	0.2667	0.2000
P21	0.3333	0.2000	0.0667	0.2667	0.1333
P22	0.2667	0.2000	0.1333	0.3333	0.0667
P23	0.3333	0.0667	0.1333	0.2667	0.2000
P24	0.2667	0.2000	0.1333	0.3333	0.0667
P25	0.3333	0.0667	0.1333	0.2667	0.2000
P26	0.3333	0.1333	0.0667	0.2667	0.2000
P27	0.2667	0.2000	0.1333	0.3333	0.0667
P28	0.2667	0.1333	0.0667	0.3333	0.2000
P29	0.2000	0.1333	0.0667	0.3333	0.2667
P30	0.3333	0.1333	0.0667	0.2000	0.2667
P31	0.2000	0.1333	0.0667	0.3333	0.2667
P32	0.3333	0.0667	0.1333	0.2000	0.2667
P33	0.2000	0.0667	0.1333	0.3333	0.2667
P34	0.2667	0.0667	0.1333	0.3333	0.2000
P35	0.2667	0.3333	0.0667	0.2000	0.1333

Geometric Mean	0.2672	0.1256	0.1041	0.2662	0.1699
Normalized weights	0.2863	0.1347	0.1116	0.2853	0.1821
Rank	1	4	5	2	3

5- Rank Reciprocal Method

I- Administrative Group

Participators	CR1	CR2	CR3	CR4	CR5

P 1	0.4380	0.0876	0.1095	0.1460	0.2190
P 2	0.1095	0.1460	0.2190	0.4380	0.0876
P 3	0.1095	0.2190	0.4380	0.1460	0.0876
P 4	0.1460	0.0876	0.1095	0.2190	0.4380
P 5	0.1460	0.0876	0.1095	0.2190	0.4380
P 6	0.4380	0.1095	0.0876	0.1460	0.2190
P 7	0.1095	0.2190	0.0876	0.4380	0.1460

P 8	0.0876	0.1095	0.1460	0.2190	0.4380
P 9	0.2190	0.1095	0.0876	0.4380	0.1460
P10	0.2190	0.1460	0.4380	0.1095	0.0876
P11	0.1095	0.4380	0.2190	0.1460	0.0876
P12	0.4380	0.0876	0.1095	0.1460	0.2190
P13	0.1460	0.1095	0.0876	0.4380	0.2190
P14	0.2190	0.1095	0.0876	0.1460	0.4380
P15	0.4380	0.1095	0.0876	0.1460	0.2190
P16	0.1460	0.1095	0.0876	0.2190	0.4380
P17	0.1460	0.1095	0.0876	0.4380	0.2190
P18	0.2190	0.1095	0.0876	0.4380	0.1460
P19	0.1095	0.0876	0.1460	0.4380	0.2190
P20	0.2190	0.1095	0.1460	0.4380	0.0876
P21	0.4380	0.1095	0.1460	0.2190	0.0876
P22	0.2190	0.0876	0.1095	0.4380	0.1460

Geometric Mean	0.1916	0.1200	0.1272	0.2476	0.1855
Normalized weights	0.2197	0.1376	0.1459	0.2841	0.2127
Rank	2	5	4	1	3

II- Academic Staff Group

Participators	CR1	CR2	CR3	CR4	CR5

P 1	0.1460	0.1095	0.0876	0.4380	0.2190
P 2	0.4380	0.1095	0.0876	0.1460	0.2190
P 3	0.2190	0.1460	0.0876	0.1095	0.4380
P 4	0.1095	0.1460	0.4380	0.2190	0.0876
P 5	0.0876	0.2190	0.4380	0.1460	0.1095
P 6	0.2190	0.4380	0.1095	0.1460	0.0876
P 7	0.2190	0.1460	0.4380	0.0876	0.1095
P 8	0.2190	0.4380	0.1095	0.0876	0.1460
P 9	0.1460	0.2190	0.0876	0.1095	0.4380
P10	0.1095	0.0876	0.4380	0.1460	0.2190
P11	0.2190	0.4380	0.1460	0.1095	0.0876
P12	0.1095	0.1460	0.2190	0.4380	0.0876
P13	0.1460	0.1095	0.4380	0.0876	0.2190
P14	0.2190	0.1460	0.0876	0.1095	0.4380
P15	0.4380	0.0876	0.1095	0.2190	0.1460
P16	0.1460	0.1095	0.2190	0.0876	0.4380

P17	0.1095	0.2190	0.1460	0.0876	0.4380
P18	0.1460	0.2190	0.4380	0.1095	0.0876
P19	0.4380	0.2190	0.1460	0.1095	0.0876
P20	0.0876	0.1095	0.1460	0.2190	0.4380
P21	0.1460	0.1095	0.4380	0.2190	0.0876
P22	0.4380	0.2190	0.1460	0.1095	0.0876
P23	0.1460	0.4380	0.2190	0.1095	0.0876
P24	0.1460	0.1095	0.0876	0.4380	0.2190
P25	0.4380	0.2190	0.1460	0.1095	0.0876
P26	0.1460	0.1095	0.0876	0.4380	0.2190
P27	0.2190	0.1095	0.0876	0.4380	0.1460
P28	0.1460	0.4380	0.2190	0.1095	0.0876
P29	0.2190	0.1460	0.0876	0.1095	0.4380
P30	0.4380	0.1095	0.0876	0.1460	0.2190
P31	0.4380	0.1095	0.0876	0.1460	0.2190
P32	0.1095	0.1460	0.2190	0.4380	0.0876
P33	0.4380	0.1095	0.1460	0.2190	0.0876
P34	0.2190	0.1095	0.0876	0.1460	0.4380
P35	0.2190	0.1095	0.0876	0.4380	0.1460
P36	0.4380	0.0876	0.1095	0.1460	0.2190
P37	0.1460	0.1095	0.0876	0.4380	0.2190
P38	0.1460	0.0876	0.4380	0.2190	0.1095

Geometric Mean	0.1975	0.1538	0.1560	0.1687	0.1680
Normalized weights	0.2340	0.1822	0.1848	0.1999	0.1991
Rank	1	5	4	2	3

III- Postgraduate Students Group

Participators	CR1	CR2	CR3	CR4	CR5

P 1	0.4380	0.2190	0.1460	0.1095	0.0876
P 2	0.4380	0.1095	0.1460	0.0876	0.2190
P 3	0.1460	0.0876	0.1095	0.2190	0.4380
P 4	0.1460	0.1095	0.0876	0.4380	0.2190
P 5	0.1460	0.1095	0.0876	0.4380	0.2190
P 6	0.1460	0.0876	0.4380	0.1095	0.2190
P 7	0.1095	0.0876	0.2190	0.4380	0.1460
P 8	0.1460	0.1095	0.0876	0.4380	0.2190
P 9	0.2190	0.1095	0.0876	0.4380	0.1460
P10	0.4380	0.1095	0.0876	0.2190	0.1460
P11	0.1460	0.1095	0.0876	0.2190	0.4380
P12	0.4380	0.1095	0.0876	0.2190	0.1460

P13	0.4380	0.1460	0.1095	0.2190	0.0876
P14	0.4380	0.1460	0.1095	0.2190	0.0876
P15	0.2190	0.0876	0.1095	0.4380	0.1460
P16	0.2190	0.1095	0.0876	0.4380	0.1460
P17	0.2190	0.1460	0.1095	0.4380	0.0876
P18	0.4380	0.0876	0.1095	0.2190	0.1460
P19	0.4380	0.1460	0.1095	0.2190	0.0876
P20	0.4380	0.1095	0.0876	0.2190	0.1460
P21	0.4380	0.1460	0.0876	0.2190	0.1095
P22	0.2190	0.1460	0.1095	0.4380	0.0876
P23	0.4380	0.0876	0.1095	0.2190	0.1460
P24	0.2190	0.1460	0.1095	0.4380	0.0876
P25	0.4380	0.0876	0.1095	0.2190	0.1460
P26	0.4380	0.1095	0.0876	0.2190	0.1460
P27	0.2190	0.1460	0.1095	0.4380	0.0876
P28	0.2190	0.1095	0.0876	0.4380	0.1460
P29	0.1460	0.1095	0.0876	0.4380	0.2190
P30	0.4380	0.1095	0.0876	0.1460	0.2190
P31	0.1460	0.1095	0.0876	0.4380	0.2190
P32	0.4380	0.0876	0.1095	0.1460	0.2190
P33	0.1460	0.0876	0.1095	0.4380	0.2190
P34	0.2190	0.0876	0.1095	0.4380	0.1460
P35	0.2190	0.4380	0.0876	0.1460	0.1095

Geometric Mean	0.2603	0.1164	0.1067	0.2719	0.1528
Normalized weights	0.2867	0.1282	0.1175	0.2994	0.1682
Rank	2	4	5	1	3

6- Rank Exponent Method

I- Administrative Group

Participators	CR1	CR2	CR3	CR4	CR5

P 1	0.4545	0.0182	0.0727	0.1636	0.2909
P 2	0.0727	0.1636	0.2909	0.4545	0.0182
P 3	0.0727	0.2909	0.4545	0.1636	0.0182
P 4	0.1636	0.0182	0.0727	0.2909	0.4545
P 5	0.1636	0.0182	0.0727	0.2909	0.4545

P 6	0.4545	0.0727	0.0182	0.1636	0.2909
P 7	0.0727	0.2909	0.0182	0.4545	0.1636
P 8	0.0182	0.0727	0.1636	0.2909	0.4545
P 9	0.2909	0.0727	0.0182	0.4545	0.1636
P10	0.2909	0.1636	0.4545	0.0727	0.0182
P11	0.0727	0.4545	0.2909	0.1636	0.0182
P12	0.4545	0.0182	0.0727	0.1636	0.2909
P13	0.1636	0.0727	0.0182	0.4545	0.2909
P14	0.2909	0.0727	0.0182	0.1636	0.4545
P15	0.4545	0.0727	0.0182	0.1636	0.2909
P16	0.1636	0.0727	0.0182	0.2909	0.4545
P17	0.1636	0.0727	0.0182	0.4545	0.2909
P18	0.2909	0.0727	0.0182	0.4545	0.1636
P19	0.0727	0.0182	0.1636	0.4545	0.2909
P20	0.2909	0.0727	0.1636	0.4545	0.0182
P21	0.4545	0.0727	0.1636	0.2909	0.0182
P22	0.2909	0.0182	0.0727	0.4545	0.1636

Geometric Mean	0.1817	0.0661	0.0640	0.2730	0.1361
Normalized weights	0.2520	0.0917	0.0888	0.3786	0.1888
Rank	2	4	5	1	3

II- Academic Staff Group

Participators	CR1	CR2	CR3	CR4	CR5

P 1	0.1636	0.0727	0.0182	0.4545	0.2909
P 2	0.4545	0.0727	0.0182	0.1636	0.2909
P 3	0.2909	0.1636	0.0182	0.0727	0.4545
P 4	0.0727	0.1636	0.4545	0.2909	0.0182
P 5	0.0182	0.2909	0.4545	0.1636	0.0727
P 6	0.2909	0.4545	0.0727	0.1636	0.0182
P 7	0.2909	0.1636	0.4545	0.0182	0.0727
P 8	0.2909	0.4545	0.0727	0.0182	0.1636
P 9	0.1636	0.2909	0.0182	0.0727	0.4545
P10	0.0727	0.0182	0.4545	0.1636	0.2909
P11	0.2909	0.4545	0.1636	0.0727	0.0182
P12	0.0727	0.1636	0.2909	0.4545	0.0182
P13	0.1636	0.0727	0.4545	0.0182	0.2909
P14	0.2909	0.1636	0.0182	0.0727	0.4545

P15	0.4545	0.0182	0.0727	0.2909	0.1636
P16	0.1636	0.0727	0.2909	0.0182	0.4545
P17	0.0727	0.2909	0.1636	0.0182	0.4545
P18	0.1636	0.2909	0.4545	0.0727	0.0182
P19	0.4545	0.2909	0.1636	0.0727	0.0182
P20	0.0182	0.0727	0.1636	0.2909	0.4545
P21	0.1636	0.0727	0.4545	0.2909	0.0182
P22	0.4545	0.2909	0.1636	0.0727	0.0182
P23	0.1636	0.4545	0.2909	0.0727	0.0182
P24	0.1636	0.0727	0.0182	0.4545	0.2909
P25	0.4545	0.2909	0.1636	0.0727	0.0182
P26	0.1636	0.0727	0.0182	0.4545	0.2909
P27	0.2909	0.0727	0.0182	0.4545	0.1636
P28	0.1636	0.4545	0.2909	0.0727	0.0182
P29	0.2909	0.1636	0.0182	0.0727	0.4545
P30	0.4545	0.0727	0.0182	0.1636	0.2909
P31	0.4545	0.0727	0.0182	0.1636	0.2909
P32	0.0727	0.1636	0.2909	0.4545	0.0182
P33	0.4545	0.0727	0.1636	0.2909	0.0182
P34	0.2909	0.0727	0.0182	0.1636	0.4545
P35	0.2909	0.0727	0.0182	0.4545	0.1636
P36	0.4545	0.0182	0.0727	0.1636	0.2909
P37	0.1636	0.0727	0.0182	0.4545	0.2909
P38	0.1636	0.0182	0.4545	0.2909	0.0727

Geometric Mean	0.1942	0.1199	0.0894	0.1316	
0.1044					
Normalized weights	0.3036	0.1875	0.1399	0.2058	0.1633
Rank	1	3	5	2	4

III- Postgraduate Students Group

Participators	CR1	CR2	CR3	CR4	CR5

P 1	0.4545	0.2909	0.1636	0.0727	0.0182
P 2	0.4545	0.0727	0.1636	0.0182	0.2909
P 3	0.1636	0.0182	0.0727	0.2909	0.4545
P 4	0.1636	0.0727	0.0182	0.4545	0.2909
P 5	0.1636	0.0727	0.0182	0.4545	0.2909
P 6	0.1636	0.0182	0.4545	0.0727	0.2909

P 7	0.0727	0.0182	0.2909	0.4545	0.1636
P 8	0.1636	0.0727	0.0182	0.4545	0.2909
P 9	0.2909	0.0727	0.0182	0.4545	0.1636
P10	0.4545	0.0727	0.0182	0.2909	0.1636
P11	0.1636	0.0727	0.0182	0.2909	0.4545
P12	0.4545	0.0727	0.0182	0.2909	0.1636
P13	0.4545	0.1636	0.0727	0.2909	0.0182
P14	0.4545	0.1636	0.0727	0.2909	0.0182
P15	0.2909	0.0182	0.0727	0.4545	0.1636
P16	0.2909	0.0727	0.0182	0.4545	0.1636
P17	0.2909	0.1636	0.0727	0.4545	0.0182
P18	0.4545	0.0182	0.0727	0.2909	0.1636
P19	0.4545	0.1636	0.0727	0.2909	0.0182
P20	0.4545	0.0727	0.0182	0.2909	0.1636
P21	0.4545	0.1636	0.0182	0.2909	0.0727
P22	0.2909	0.1636	0.0727	0.4545	0.0182
P23	0.4545	0.0182	0.0727	0.2909	0.1636
P24	0.2909	0.1636	0.0727	0.4545	0.0182
P25	0.4545	0.0182	0.0727	0.2909	0.1636
P26	0.4545	0.0727	0.0182	0.2909	0.1636
P27	0.2909	0.1636	0.0727	0.4545	0.0182
P28	0.2909	0.0727	0.0182	0.4545	0.1636
P29	0.1636	0.0727	0.0182	0.4545	0.2909
P30	0.4545	0.0727	0.0182	0.1636	0.2909
P31	0.1636	0.0727	0.0182	0.4545	0.2909
P32	0.4545	0.0182	0.0727	0.1636	0.2909
P33	0.1636	0.0182	0.0727	0.4545	0.2909
P34	0.2909	0.0182	0.0727	0.4545	0.1636
P35	0.2909	0.4545	0.0182	0.1636	0.0727

Geometric Mean	0.2920	0.0646	0.0443	0.2898	0.1181
Normalized weights	0.3610	0.0798	0.0548	0.3583	0.1461
Rank	1	4	5	2	3

7- Rank Order Centroid Method

I- Administrative Group

Participators	CR1	CR2	CR3	CR4	CR5

P 1	0.4567	0.0400	0.0900	0.1567	0.2567

P 2	0.0900	0.1567	0.2567	0.4567	0.0400
P 3	0.0900	0.2567	0.4567	0.1567	0.0400
P 4	0.1567	0.0400	0.0900	0.2567	0.4567
P 5	0.1567	0.0400	0.0900	0.2567	0.4567
P 6	0.4567	0.0900	0.0400	0.1567	0.2567
P 7	0.0900	0.2567	0.0400	0.4567	0.1567
P 8	0.0400	0.0900	0.1567	0.2567	0.4567
P 9	0.2567	0.0900	0.0400	0.4567	0.1567
P10	0.2567	0.1567	0.4567	0.0900	0.0400
P11	0.0900	0.4567	0.2567	0.1567	0.0400
P12	0.4567	0.0400	0.0900	0.1567	0.2567
P13	0.1567	0.0900	0.0400	0.4567	0.2567
P14	0.2567	0.0900	0.0400	0.1567	0.4567
P15	0.4567	0.0900	0.0400	0.1567	0.2567
P16	0.1567	0.0900	0.0400	0.2567	0.4567
P17	0.1567	0.0900	0.0400	0.4567	0.2567
P18	0.2567	0.0900	0.0400	0.4567	0.1567
P19	0.0900	0.0400	0.1567	0.4567	0.2567
P20	0.2567	0.0900	0.1567	0.4567	0.0400
P21	0.4567	0.0900	0.1567	0.2567	0.0400
P22	0.2567	0.0400	0.0900	0.4567	0.1567

Geometric Mean	0.1894	0.0898	0.0911	0.2647	0.1611
Normalized weights	0.2379	0.1129	0.1144	0.3325	0.2023
Rank	2	5	4	1	3

II- Academic Staff Group

Participators	CR1	CR2	CR3	CR4	CR5

P 1	0.1567	0.0900	0.0400	0.4567	0.2567
P 2	0.4567	0.0900	0.0400	0.1567	0.2567
P 3	0.2567	0.1567	0.0400	0.0900	0.4567
P 4	0.0900	0.1567	0.4567	0.2567	0.0400
P 5	0.0400	0.2567	0.4567	0.1567	0.0900
P 6	0.2567	0.4567	0.0900	0.1567	0.0400
P 7	0.2567	0.1567	0.4567	0.0400	0.0900
P 8	0.2567	0.4567	0.0900	0.0400	0.1567
P 9	0.1567	0.2567	0.0400	0.0900	0.4567
P10	0.0900	0.0400	0.4567	0.1567	0.2567
P11	0.2567	0.4567	0.1567	0.0900	0.0400

P12	0.0900	0.1567	0.2567	0.4567	0.0400
P13	0.1567	0.0900	0.4567	0.0400	0.2567
P14	0.2567	0.1567	0.0400	0.0900	0.4567
P15	0.4567	0.0400	0.0900	0.2567	0.1567
P16	0.1567	0.0900	0.2567	0.0400	0.4567
P17	0.0900	0.2567	0.1567	0.0400	0.4567
P18	0.1567	0.2567	0.4567	0.0900	0.0400
P19	0.4567	0.2567	0.1567	0.0900	0.0400
P20	0.0400	0.0900	0.1567	0.2567	0.4567
P21	0.1567	0.0900	0.4567	0.2567	0.0400
P22	0.4567	0.2567	0.1567	0.0900	0.0400
P23	0.1567	0.4567	0.2567	0.0900	0.0400
P24	0.1567	0.0900	0.0400	0.4567	0.2567
P25	0.4567	0.2567	0.1567	0.0900	0.0400
P26	0.1567	0.0900	0.0400	0.4567	0.2567
P27	0.2567	0.0900	0.0400	0.4567	0.1567
P28	0.1567	0.4567	0.2567	0.0900	0.0400
P29	0.2567	0.1567	0.0400	0.0900	0.4567
P30	0.4567	0.0900	0.0400	0.1567	0.2567
P31	0.4567	0.0900	0.0400	0.1567	0.2567
P32	0.0900	0.1567	0.2567	0.4567	0.0400
P33	0.4567	0.0900	0.1567	0.2567	0.0400
P34	0.2567	0.0900	0.0400	0.1567	0.4567
P35	0.2567	0.0900	0.0400	0.4567	0.1567
P36	0.4567	0.0400	0.0900	0.1567	0.2567
P37	0.1567	0.0900	0.0400	0.4567	0.2567
P38	0.1567	0.0400	0.4567	0.2567	0.0900

Geometric Mean	0.1989	0.1375	0.1195	0.1510	0.1341
Normalized weights	0.2684	0.1855	0.1612	0.2038	0.1810
Rank	1	3	5	2	4

III- Postgraduate Students Group

Participators	CR1	CR2	CR3	CR4	CR5

P 1	0.4567	0.2567	0.1567	0.0900	0.0400
P 2	0.4567	0.0900	0.1567	0.0400	0.2567
P 3	0.1567	0.0400	0.0900	0.2567	0.4567
P 4	0.1567	0.0900	0.0400	0.4567	0.2567
P 5	0.1567	0.0900	0.0400	0.4567	0.2567

P 6	0.1567	0.0400	0.4567	0.0900	0.2567
P 7	0.0900	0.0400	0.2567	0.4567	0.1567
P 8	0.1567	0.0900	0.0400	0.4567	0.2567
P 9	0.2567	0.0900	0.0400	0.4567	0.1567
P10	0.4567	0.0900	0.0400	0.2567	0.1567
P11	0.1567	0.0900	0.0400	0.2567	0.4567
P12	0.4567	0.0900	0.0400	0.2567	0.1567
P13	0.4567	0.1567	0.0900	0.2567	0.0400
P14	0.4567	0.1567	0.0900	0.2567	0.0400
P15	0.2567	0.0400	0.0900	0.4567	0.1567
P16	0.2567	0.0900	0.0400	0.4567	0.1567
P17	0.2567	0.1567	0.0900	0.4567	0.0400
P18	0.4567	0.0400	0.0900	0.2567	0.1567
P19	0.4567	0.1567	0.0900	0.2567	0.0400
P20	0.4567	0.0900	0.0400	0.2567	0.1567
P21	0.4567	0.1567	0.0400	0.2567	0.0900
P22	0.2567	0.1567	0.0900	0.4567	0.0400
P23	0.4567	0.0400	0.0900	0.2567	0.1567
P24	0.2567	0.1567	0.0900	0.4567	0.0400
P25	0.4567	0.0400	0.0900	0.2567	0.1567
P26	0.4567	0.0900	0.0400	0.2567	0.1567
P27	0.2567	0.1567	0.0900	0.4567	0.0400
P28	0.2567	0.0900	0.0400	0.4567	0.1567
P29	0.1567	0.0900	0.0400	0.4567	0.2567
P30	0.4567	0.0900	0.0400	0.1567	0.2567
P31	0.1567	0.0900	0.0400	0.4567	0.2567
P32	0.4567	0.0400	0.0900	0.1567	0.2567
P33	0.1567	0.0400	0.0900	0.4567	0.2567
P34	0.2567	0.0400	0.0900	0.4567	0.1567
P35	0.2567	0.4567	0.0400	0.1567	0.0900

Geometric Mean	0.2809	0.0875	0.0692	0.2860	0.1360
Normalized weights	0.3268	0.1018	0.0805	0.3327	0.1582
Rank	2	4	5	1	3

8- Graphical Method

I- Administrative Group

Participators	CR1	CR2	CR3	CR4	CR5

P 1	0.4626	0.0474	0.0881	0.1487	0.2533
P 2	0.0807	0.1848	0.2881	0.3628	0.0837
P 3	0.1463	0.1786	0.3187	0.3113	0.0451
P 4	0.1454	0.0480	0.0884	0.2762	0.4420
P 5	0.1716	0.0421	0.0755	0.3219	0.3889
P 6	0.3823	0.0962	0.0370	0.1928	0.2918
P 7	0.0928	0.2647	0.0481	0.3797	0.2147
P 8	0.0562	0.0974	0.1684	0.2835	0.3945
P 9	0.2248	0.1398	0.0422	0.4283	0.1649
P10	0.2505	0.1869	0.4139	0.1059	0.0429
P11	0.0749	0.4812	0.2566	0.1482	0.0391
P12	0.4143	0.0499	0.0909	0.1572	0.2877
P13	0.1996	0.2562	0.4070	0.0479	0.0893
P14	0.0924	0.1705	0.1918	0.1490	0.3963
P15	0.3745	0.0916	0.0363	0.2119	0.2858
P16	0.1784	0.0702	0.0715	0.2495	0.4305
P17	0.1915	0.0754	0.0969	0.4086	0.2277
P18	0.2564	0.2111	0.3062	0.1742	0.0520
P19	0.1147	0.0427	0.1767	0.3837	0.2822
P20	0.3141	0.0856	0.1425	0.4115	0.0464
P21	0.4483	0.0799	0.1331	0.2955	0.0432
P22	0.2647	0.0481	0.0928	0.4143	0.1802

Geometric Mean	0.1891	0.1052	0.1244	0.2367	0.1557
Normalized weights	0.2332	0.1297	0.1534	0.2917	0.1919
Rank	2	5	4	1	3

II- Academic Staff Group

Participators	CR1	CR2	CR3	CR4	CR5

P 1	0.0873	0.0473	0.3978	0.3204	0.1472
P 2	0.4276	0.0484	0.0889	0.1537	0.2813

P 3	0.0384	0.4171	0.2571	0.1049	0.1825
P 4	0.1536	0.0906	0.1500	0.4272	0.1787
P 5	0.1595	0.2685	0.1011	0.0507	0.4203
P 6	0.2704	0.4232	0.0948	0.1606	0.0510
P 7	0.0957	0.4143	0.2877	0.0909	0.1114
P 8	0.3049	0.4065	0.0490	0.1504	0.0892
P 9	0.0490	0.2446	0.4065	0.0892	0.2107
P10	0.0575	0.1723	0.1017	0.4036	0.2649
P11	0.3430	0.3562	0.1698	0.0936	0.0374
P12	0.0876	0.1401	0.2679	0.4562	0.0482
P13	0.1185	0.0707	0.4278	0.0420	0.3410
P14	0.2783	0.1572	0.0436	0.0825	0.4384
P15	0.4163	0.1478	0.0546	0.1811	0.2003
P16	0.1460	0.0859	0.2451	0.0469	0.4760
P17	0.0504	0.2706	0.1607	0.0948	0.4235
P18	0.1727	0.2978	0.3970	0.0871	0.0454
P19	0.4143	0.2647	0.1802	0.0928	0.0481
P20	0.0481	0.0928	0.1802	0.2992	0.3797
P21	0.1719	0.0983	0.4520	0.2423	0.0356
P22	0.3900	0.2709	0.2130	0.0819	0.0442
P23	0.1903	0.3595	0.2855	0.1286	0.0362
P24	0.1730	0.1080	0.0425	0.4108	0.2657
P25	0.4132	0.2899	0.1649	0.0859	0.0461
P26	0.1852	0.2680	0.3785	0.0461	0.1221
P27	0.3085	0.1053	0.0402	0.3262	0.2198
P28	0.1608	0.4356	0.2800	0.0813	0.0423
P29	0.2640	0.2011	0.0490	0.1340	0.3519
P30	0.3684	0.0819	0.0442	0.2167	0.2888
P31	0.3765	0.1000	0.0391	0.2230	0.2615
P32	0.1089	0.1911	0.2706	0.3896	0.0398
P33	0.3970	0.0871	0.1727	0.2978	0.0454
P34	0.2745	0.0791	0.0415	0.1576	0.4473
P35	0.2649	0.1066	0.0386	0.4027	0.1872
P36	0.3602	0.0414	0.1144	0.2026	0.2814
P37	0.2026	0.1144	0.0414	0.3602	0.2814
P38	0.2074	0.0488	0.3687	0.2880	0.0871

Geometric Mean	0.1841	0.1555	0.1371	0.1571	0.1396
Normalized weights	0.2381	0.2010	0.1773	0.2031	0.1805
Rank	1	3	5	2	4

III- Postgraduate Students Group

Participators	CR1	CR2	CR3	CR4	CR5

P 1	0.4088	0.2725	0.1993	0.0789	0.0405
P 2	0.4147	0.1555	0.2880	0.0910	0.0507
P 3	0.1747	0.0471	0.0908	0.2592	0.4282
P 4	0.1639	0.1064	0.0415	0.2199	0.4683
P 5	0.1508	0.0850	0.0347	0.3979	0.3315
P 6	0.0855	0.0466	0.4331	0.1425	0.2923
P 7	0.1066	0.0386	0.2649	0.4027	0.1872
P 8	0.1709	0.0889	0.0454	0.4191	0.2757
P 9	0.2800	0.0813	0.0423	0.4356	0.1608
P10	0.3922	0.0726	0.0384	0.3040	0.1928
P11	0.2196	0.0672	0.0356	0.2877	0.3898
P12	0.3519	0.1340	0.0490	0.2640	0.2011
P13	0.3940	0.1682	0.1005	0.2832	0.0542
P14	0.4000	0.1842	0.1235	0.2471	0.0452
P15	0.2822	0.0427	0.1147	0.3837	0.1767
P16	0.2647	0.0928	0.0481	0.4143	0.1802
P17	0.2978	0.1727	0.0871	0.3970	0.0454
P18	0.4002	0.0518	0.0930	0.2943	0.1608
P19	0.4423	0.1413	0.0990	0.2580	0.0595
P20	0.4411	0.0865	0.0479	0.2757	0.1489
P21	0.3940	0.1682	0.0542	0.2832	0.1005
P22	0.2447	0.1759	0.1095	0.4121	0.0579
P23	0.4356	0.0423	0.0813	0.2800	0.1608
P24	0.2757	0.1489	0.0865	0.4411	0.0479
P25	0.3851	0.0608	0.1047	0.2953	0.1540
P26	0.4511	0.0753	0.0416	0.3040	0.1281
P27	0.2647	0.1554	0.0928	0.4373	0.0499
P28	0.2832	0.1005	0.0542	0.3940	0.1682
P29	0.2160	0.0817	0.0434	0.3672	0.2916
P30	0.3597	0.0955	0.0352	0.2198	0.2898
P31	0.2003	0.0764	0.0406	0.4076	0.2751
P32	0.3687	0.0488	0.0871	0.2074	0.2880
P33	0.1755	0.0415	0.0746	0.4612	0.2472
P34	0.2757	0.0479	0.0865	0.4411	0.1489
P35	0.2916	0.3348	0.0434	0.2484	0.0817

Geometric Mean	0.2774	0.0919	0.0749	0.2951	0.1443
Normalized weights	0.3140	0.1041	0.0848	0.3339	0.1633
Rank	2	4	5	1	3

9- Pairwise Comparisons Method

I- Administrative Group

Participators	CR1	CR2	CR3	CR4	CR5

P 1	0.4810	0.0490	0.0820	0.1380	0.2500
P 2	0.0750	0.1590	0.2970	0.4190	0.0500
P 3	0.1210	0.0860	0.3010	0.4500	0.0420
P 4	0.1280	0.0500	0.0820	0.2730	0.4670
P 5	0.1230	0.0370	0.0590	0.2740	0.5070
P 6	0.4400	0.0780	0.0400	0.1520	0.2900
P 7	0.0840	0.2300	0.0470	0.4930	0.1450
P 8	0.0610	0.0860	0.1550	0.2720	0.4270
P 9	0.2390	0.0930	0.0470	0.4780	0.1420
P10	0.2660	0.1530	0.4480	0.0870	0.0470
P11	0.0680	0.5320	0.2320	0.1270	0.0400
P12	0.4400	0.0520	0.0830	0.1500	0.2750
P13	0.1650	0.2420	0.4620	0.0510	0.0810
P14	0.0960	0.2770	0.3880	0.1830	0.0560
P15	0.4420	0.0720	0.0390	0.1730	0.2740
P16	0.1380	0.0650	0.0410	0.2480	0.5080
P17	0.1350	0.0590	0.0400	0.4590	0.3080
P18	0.2180	0.0850	0.0410	0.5230	0.1330
P19	0.1000	0.0440	0.1610	0.4250	0.2700
P20	0.2970	0.0790	0.1260	0.4500	0.0480
P21	0.4810	0.0740	0.1160	0.2840	0.0450
P22	0.2600	0.0490	0.0880	0.4420	0.1610

Geometric Mean	0.1781	0.0921	0.1067	0.2566	0.1427
Normalized weights	0.2294	0.1187	0.1375	0.3305	0.1839
Rank	2	5	4	1	3

II- Academic Staff Group

Participators	CR1	CR2	CR3	CR4	CR5

P 1	0.0800	0.0490	0.4320	0.3040	0.1360
P 2	0.4470	0.0500	0.0820	0.1490	0.2730
P 3	0.0400	0.4870	0.2340	0.0890	0.1490
P 4	0.1510	0.0840	0.2780	0.4330	0.0540
P 5	0.1520	0.2620	0.0890	0.0520	0.4450
P 6	0.2620	0.4450	0.0890	0.1520	0.0520
P 7	0.1050	0.3240	0.1900	0.0570	0.3240
P 8	0.2970	0.4340	0.0510	0.1370	0.0810
P 9	0.0510	0.1990	0.4290	0.0810	0.2400
P10	0.0610	0.1570	0.0920	0.4310	0.2580
P11	0.3070	0.4430	0.1380	0.0720	0.0400
P12	0.0820	0.1140	0.2550	0.4990	0.0510
P13	0.0990	0.0660	0.4930	0.0430	0.2980
P14	0.2560	0.1240	0.0460	0.0760	0.4990
P15	0.4280	0.0410	0.0810	0.2750	0.1760
P16	0.1340	0.0770	0.2250	0.0490	0.5150
P17	0.0520	0.2620	0.1520	0.0890	0.4450
P18	0.1570	0.2800	0.4350	0.0810	0.0470
P19	0.4420	0.2600	0.1610	0.0880	0.0490
P20	0.0490	0.0880	0.1590	0.3610	0.3430
P21	0.1440	0.0840	0.5090	0.2270	0.0370
P22	0.4320	0.2690	0.1790	0.0750	0.0450
P23	0.1800	0.4000	0.2780	0.1050	0.0370
P24	0.1350	0.0570	0.0720	0.6300	0.1050
P25	0.4770	0.2640	0.1330	0.0770	0.0490
P26	0.1610	0.2460	0.4380	0.0470	0.1080
P27	0.2810	0.0800	0.0400	0.4770	0.1230
P28	0.1430	0.4710	0.2680	0.0750	0.0440
P29	0.2590	0.1870	0.0500	0.1220	0.3820
P30	0.4310	0.0730	0.0450	0.1900	0.2610
P31	0.4190	0.0810	0.0420	0.1790	0.2800
P32	0.0940	0.1650	0.2640	0.4360	0.0420
P33	0.4350	0.0810	0.1570	0.2800	0.0470
P34	0.2640	0.0720	0.0430	0.1410	0.4800
P35	0.2620	0.0930	0.0400	0.4420	0.1630
P36	0.3970	0.0420	0.1010	0.1840	0.2760
P37	0.1840	0.1010	0.0420	0.3970	0.2760
P38	0.1900	0.0510	0.4000	0.2810	0.0770

Geometric					

Mean	0.1797	0.1407	0.1377	0.1539	0.1314
Normalized weights	0.2418	0.1893	0.1852	0.2070	0.1767
Rank	1	3	4	2	5

III- Postgraduate Students Group

Participators	CR1	CR2	CR3	CR4	CR5

P 1	0.4840	0.2390	0.1610	0.0750	0.0410
P 2	0.4520	0.1410	0.2710	0.0820	0.0530
P 3	0.1500	0.0490	0.0860	0.2540	0.4620
P 4	0.1370	0.0900	0.0440	0.2150	0.5140
P 5	0.1000	0.0540	0.0460	0.4000	0.4000
P 6	0.0800	0.0480	0.4580	0.1260	0.2870
P 7	0.0930	0.0400	0.2620	0.4420	0.1630
P 8	0.1480	0.0850	0.0460	0.4590	0.2610
P 9	0.2680	0.0780	0.0440	0.4710	0.1430
P10	0.4400	0.0660	0.0400	0.2860	0.1690
P11	0.1830	0.0610	0.0370	0.2800	0.4400
P12	0.3820	0.1220	0.0500	0.2590	0.1870
P13	0.4250	0.1560	0.0950	0.2690	0.0550
P14	0.4310	0.1660	0.1110	0.2460	0.0460
P15	0.2700	0.0440	0.1000	0.4250	0.1610
P16	0.2600	0.0880	0.0490	0.4420	0.1610
P17	0.2800	0.1570	0.0810	0.4350	0.0470
P18	0.4330	0.0540	0.0840	0.2780	0.1510
P19	0.4610	0.1350	0.0910	0.2520	0.0620
P20	0.4690	0.0780	0.0510	0.2650	0.1380
P21	0.4250	0.1560	0.0550	0.2690	0.0950
P22	0.2430	0.1610	0.1060	0.4310	0.0590
P23	0.4710	0.0440	0.0750	0.2680	0.1430
P24	0.2650	0.1380	0.0780	0.4690	0.0510
P25	0.4020	0.0620	0.0980	0.2770	0.1620
P26	0.4850	0.0670	0.0440	0.2910	0.1130
P27	0.2560	0.1420	0.0870	0.4640	0.0520
P28	0.2690	0.0950	0.0550	0.4250	0.1560
P29	0.1940	0.0750	0.0440	0.4030	0.2840
P30	0.4030	0.0800	0.0370	0.1960	0.2850
P31	0.1730	0.0700	0.0420	0.4460	0.2700
P32	0.4000	0.0510	0.0770	0.1900	0.2810
P33	0.1490	0.0440	0.0650	0.5110	0.2310

P34	0.2650	0.0510	0.0780	0.4690	0.1380
P35	0.2900	0.3170	0.0430	0.2780	0.0720

Geometric Mean	0.2713	0.0861	0.0727	0.2956	0.1418
Normalized weights	0.3127	0.0993	0.0838	0.3407	0.1635
Rank	2	4	5	1	3



Appendix G

MATLAB Program for Calculating Criteria Weights

```

clc;
clear all
n=9;          %***** number of method

N=input('Input the number of Criteria:');
%NB= input('Input the number of ibers:');

p=input('Input the power of exponent: ')
for i=1:N
    % name(i,:)= input('the name of criteia:', 's');
end
fpp=0;
fgm=0;
Nf=input('Input the number of files:');
disp('##### Starting the Rating Method #####')

for fp=1:Nf

    nam{fp}= input('the name of data file:', 's');
    end
    for fp=1:Nf
        a=xlsread(nam{fp})
        sz=size(a);
        Np=sz(1);

        %***** Rating Method *****
        for jj=1:Np
            Ri=a(jj,:);
            original_weight=Ri/min(Ri);
            Wi_ratingadm(jj,:)=Ri/sum(Ri);
            %Wi_ratingadmsm(jj)=sum(Wi_ratingadm(jj,:));
            end
            fpp=fpp+1;
            mmt{fpp}=Wi_ratingadm;
            for i=1:N
                fg=1;
                for j=1:Np
                    fg=fg*Wi_ratingadm(j,i);
                end
                G_M(i)=power(fg,1/Np);
            end
            G_Mrating(fp,:)=G_M;
            G_MM(fpp,:)=G_M;
            clear Ri
            clear Wi_ratingadm
            clear a
            end
            gmr=sum(G_Mrating');
            for k=1:Nf
                G_Mratingnor(k,:)=G_Mrating(k,:)./gmr(k);
            end
            G_MMnor(fpp-Nf+1:fpp,:)=G_Mratingnor;

```

```

for i=1:N
    fg=1;
    for j=1:Nf
        fg=fg*G_Mrating(j,i);
    end
    G_Mratingall(i)=power(fg,1/Nf);
end

G_Mratingallnorm=G_Mratingall/sum(G_Mratingall);
fgm=fgm+1;
GM_all(fgm,:)=G_Mratingallnorm;
close all;
%***** Ratio Method *****

disp('##### Starting the Ratio Method #####')

for fp=1:Nf

    nam{fp}= input('the name of data file:', 's');
    end
    for fpp=1:Nf
        a=xlsread(nam{fp})
        sz=size(a);
        Np=sz(1);

        for jj=1:Np
            Ri=a(jj,:);
            Wi_ratio(jj,:)=Ri/sum(Ri);
            Wi_ratiosm(jj)=sum(Wi_ratio(jj,:));
            end
            fpp=fpp+1;
            mmt{fpp}=Wi_ratio;
            for i=1:N
                fg=1;
                for j=1:Np
                    fg=fg*Wi_ratio(j,i);
                end
                G_M(i)=power(fg,1/Np);
            end
            G_Mratio(fp,:)=G_M;
            G_MM(fpp,:)=G_M;
            clear Ri
            clear Wi_ratio
            clear a
            end
            gmr=sum(G_Mratio');
            for k=1:Nf
                G_Mrationor(k,:)=G_Mratio(k,:)./gmr(k);
            end
            G_MMnor(fpp-Nf+1:fpp,:)=G_Mrationor;
            for i=1:N
                fg=1;
                for j=1:Nf
                    fg=fg*G_Mratio(j,i);
                end
                G_Mratioall(i)=power(fg,1/Nf);
            end

```

```

G_Mratioallnorm=G_Mratioall/sum(G_Mratioall);

fgm=fgm+1;
GM_all(fgm,:)=G_Mratioallnorm;

close all;
%***** Point allocation Method *****

disp('##### Starting the Point allocation Method #####')

for fp=1:Nf

nam{fp}= input('the name of data file:', 's');
end
for fp=1:Nf
a=xlsread(nam{fp})
sz=size(a);
Np=sz(1);

for jj=1:Np
Ri=a(jj,:);
Wi_point(jj,:)=Ri/sum(Ri);
Wi_pointsm(jj)=sum(Wi_point(jj,:));
end
fpp=fpp+1;
mmt{fpp}=Wi_point;
for i=1:N
    fg=1;
    for j=1:Np
        fg=fg*Wi_point(j,i);
    end
    G_M(i)=power(fg,1/Np);
end
G_Mpoint(fp,:)=G_M;
G_MM(fpp,:)=G_M;
clear Ri
clear Wi_point
clear a
end
gmr=sum(G_Mpoint');
for k=1:Nf
    G_Mpointnor(k,:)=G_Mpoint(k,:)./gmr(k);
end
G_MMnor(fpp-Nf+1:fpp,:)=G_Mpointnor;
for i=1:N
    fg=1;
    for j=1:Nf
        fg=fg*G_Mpoint(j,i);
    end
    G_Mpointall(i)=power(fg,1/Nf);
end

G_Mpointallnorm=G_Mpointall/sum(G_Mpointall);

```

```

fgm=fgm+1;
GM_all(fgm,:)=G_Mpointallnorm;

close all;
%***** Rank sum Weight Method *****

disp('##### Starting the Rank sum weight Method #####')

for fp=1:Nf

nam{fp}= input('the name of data file:', 's');
end
for fp=1:Nf
a=xlsread(nam{fp})
sz=size(a);
Np=sz(1);

for jj=1:Np
Ri=a(jj,:);

sr=sort(Ri,'descend');
k=1;
for i=1:N
for j=1:N
if sr(i)==Ri(j)
ri(j)=Ri(j);
%k=k+1;
end
end
end

for i=1:N
Nri(i)=N-ri(i)+1;
end
Wi_Rank(jj,:)=Nri/sum(Nri)
Wi_Ranksm(jj)=sum(Wi_Rank(jj,:));
end
fpp=fpp+1;
mmt{fpp}=Wi_Rank;
for i=1:N
fg=1;
for j=1:Np
fg=fg*Wi_Rank(j,i);
end
G_M(i)=power(fg,1/Np);
end
G_Mrank(fp,:)=G_M;
G_MM(fpp,:)=G_M;
clear Ri
clear Wi_Rank
clear a
end
gmr=sum(G_Mrank');
for k=1:Nf
G_Mranknor(k,:)=G_Mrank(k,:)./gmr(k);
end
G_MMnor(fpp-Nf+1:fpp,:)=G_Mranknor;
for i=1:N
fg=1;

```

```

for j=1:Nf
    fg=fg*G_Mrank(j,i);
end
G_Mrankall(i)=power(fg,1/Nf);
end

G_Mrankallnorm=G_Mrankall/sum(G_Mrankall);

fgm=fgm+1;
GM_all(fgm,:)=G_Mrankallnorm;

%***** Rank Reciprocal Method *****

disp('##### Starting the Rank reciprocal Method #####')

for fp=1:Nf
a=xlsread(nam{fp})
sz=size(a);
Np=sz(1);

for jj=1:Np
Ri=a(jj,:);

sr=sort(Ri,'descend');
k=1;
for i=1:N
    for j=1:N
        if sr(i)==Ri(j)
            ri(j)=Ri(j);
            %k=k+1;
        end
    end
end

for i=1:N
Nri(i)=1./ri(i);
end

Wi_Rankreciprocal(jj,:)=Nri/sum(Nri)
Wi_Rankreciprocalsm(jj)=sum(Wi_Rankreciprocal(jj,:));
end
fpp=fpp+1;
mmt{fpp}=Wi_Rankreciprocal;
for i=1:N
    fg=1;
    for j=1:Np
        fg=fg*Wi_Rankreciprocal(j,i);
    end
    G_M(i)=power(fg,1/Np);
end
G_Mrankreciprocal(fp,:)=G_M;
G_MM(fpp,:)=G_M;
clear Ri
clear Wi_Rankreciprocal
clear a
end

```

```

gmr=sum(G_Mrankreciprocal');
for k=1:Nf
    G_Mrankreciprocalnor(k,:)=G_Mrankreciprocal(k,:)./gmr(k);
end
G_MMnor(fpp-Nf+1:fpp,:)=G_Mrankreciprocalnor;
for i=1:N
    fg=1;
    for j=1:Nf
        fg=fg*G_Mrankreciprocal(j,i);
    end
    G_Mrankreciprocalall(i)=power(fg,1/Nf);
end

G_Mrankreciprocalallnorm=G_Mrankreciprocalall/sum(G_Mrankreciprocalall);

fgm=fgm+1;
GM_all(fgm,:)=G_Mrankreciprocalallnorm;

%***** Rank Exponent Method *****

disp('##### Starting the Rank exponent Method #####')

for fp=1:Nf
    a=xlsread(nam{fp})
    sz=size(a);
    Np=sz(1);

    for jj=1:Np
        Ri=a(jj,:);

        sr=sort(Ri,'descend');
        k=1;
        for i=1:N
            for j=1:N
                if sr(i)==Ri(j)
                    ri(j)=Ri(j);
                    %k=k+1;
                end
            end
        end

        for i=1:N
            mm=N-ri(i)+1;
            Nri(i)=power(mm,p);
        end

        Wi_Rankexponent(jj,:)=Nri/sum(Nri)
        Wi_Rankexponentsm(jj)=sum(Wi_Rankexponent(jj,:));
    end
    fpp=fpp+1;
    mmt{fpp}=Wi_Rankexponent;
    for i=1:N
        fg=1;
        for j=1:Np
            fg=fg*Wi_Rankexponent(j,i);
        end
        G_M(i)=power(fg,1/Np);
    end
end

```

```

end
G_Mrankexponent(fp,:)=G_M;
G_MM(fpp,:)=G_M;
clear Ri
clear Wi_Rankexponent
clear a
end
gmr=sum(G_Mrankexponent');
for k=1:Nf
    G_Mrankexponentnor(k,:)=G_Mrankexponent(k,:)./gmr(k);
end
G_MMnor(fpp-Nf+1:fpp,:)=G_Mrankexponentnor;
for i=1:N
    fg=1;
    for j=1:Nf
        fg=fg*G_Mrankexponent(j,i);
    end
    G_Mrankexponentall(i)=power(fg,1/Nf);
end

G_Mrankexponentallnorm=G_Mrankexponentall/sum(G_Mrankexponentall);

fgm=fgm+1;
GM_all(fgm,:)=G_Mrankexponentallnorm;

%***** Rank-order Centroid Method *****

disp('##### Starting the Rank-order centroid Method #####')

for fp=1:Nf
a=xlsread(nam{fp})
sz=size(a);
Np=sz(1);

for jj=1:Np
Ri=a(jj,:);

sr=sort(Ri,'descend');
k=1;
for i=1:N
    for j=1:N
        if sr(i)==Ri(j)
            ri(j)=Ri(j);
        end
    end
end

for i=1:N
    sm=0;
    for j=ri(i):N
        sm=sm+1/j;
    end

Nri(i)=sm/N;
end

```

```

Wi_Rankcentroid(jj,:)=Nri;
Wi_Rankcentroids(m(jj))=sum(Wi_Rankcentroid(jj,:));
end
fpp=fpp+1;
mmt{fpp}=Wi_Rankcentroid;
for i=1:N
    fg=1;
    for j=1:Np
        fg=fg*Wi_Rankcentroid(j,i);
    end
    G_M(i)=power(fg,1/Np);
end
G_Mrankcentroid(fp,:)=G_M;
G_MM(fpp,:)=G_M;
clear Ri
clear Wi_Rankcentroid
clear a
end
gmr=sum(G_Mrankcentroid');
for k=1:Nf
    G_Mrankcentroidnor(k,:)=G_Mrankcentroid(k,:)./gmr(k);
end
G_MMnor(fpp-Nf+1:fpp,:)=G_Mrankcentroidnor;
for i=1:N
    fg=1;
    for j=1:Nf
        fg=fg*G_Mrankcentroid(j,i);
    end
    G_Mrankcentroidall(i)=power(fg,1/Nf);
end

G_Mrankcentroidallnorm=G_Mrankcentroidall/sum(G_Mrankcentroidall);

fgm=fgm+1;
GM_all(fgm,:)=G_Mrankcentroidallnorm;

close all;
%***** Graphical Weighting Method *****

disp('##### Starting the Graphical weighting Method #####')

for fp=1:Nf

nam{fp}= input('the name of data file:', 's');
end
for fp=1:Nf
a=xlsread(nam{fp})
sz=size(a);
Np=sz(1)/N;
jk=1;
for jj=1:N:N*Np

```

```

for k=1:N

Rin(k,:)=a(jj+(k-1),:);
end

srw=sum(Rin');

Wi_graphical(jk,:)=srw/sum(srw);
Wi_graphicalsm(jk)=sum(Wi_graphical(jk,:));
jk=jk+1;
end
fpp=fpp+1;
mmt{fpp}=Wi_graphical;
for i=1:N
    fg=1;
    for j=1:Np
        fg=fg*Wi_graphical(j,i);
    end
    G_M(i)=power(fg,1/Np);
end
G_Mgraphical(fp,:)=G_M;
G_MM(fpp,:)=G_M;
clear Rin
clear Wi_graphical
clear a
end
gmr=sum(G_Mgraphical');
for k=1:Nf
    G_Mgraphicalnor(k,:)=G_Mgraphical(k,:)./gmr(k);
end
G_MMnor(fpp-Nf+1:fpp,:)=G_Mgraphicalnor;
for i=1:N
    fg=1;
    for j=1:Nf
        fg=fg*G_Mgraphical(j,i);
    end
    G_Mgraphicalall(i)=power(fg,1/Nf);
end

G_Mgraphicalallnorm=G_Mgraphicalall/sum(G_Mgraphicalall);

fgm=fgm+1;
GM_all(fgm,:)=G_Mgraphicalallnorm;

disp('##### Starting the PAIRWISE Method #####')

for fp=1:Nf

nam{fp}= input('the name of data file:', 's');
end
for fp=1:Nf
a=xlsread(nam{fp})

```

```

sz=size(a);
Np=sz(1);

for jj=1:Np
Ri=a(jj,:);

Wi_pairwise(jj,:)=Ri;
Wi_pairwisesm(jj)=sum(Wi_pairwise(jj,:));
end
fpp=fpp+1;
mmt{fpp}=Wi_pairwise;
for i=1:N
    fg=1;
    for j=1:Np
        fg=fg*Wi_pairwise(j,i);
    end
    G_M(i)=power(fg,1/Np);
end
G_Mpairwise(fp,:)=G_M;
G_MM(fpp,:)=G_M;
clear Rin
clear Wi_pairwise
clear a
end
gmr=sum(G_Mpairwise');
for k=1:Nf
    G_Mpairwisenor(k,:)=G_Mpairwise(k,:)./gmr(k);
end
G_MMnor(fpp-Nf+1:fpp,:)=G_Mpairwisenor;

for i=1:N
    fg=1;
    for j=1:Nf
        fg=fg*G_Mpairwise(j,i);
    end
    G_Mpairwiseall(i)=power(fg,1/Nf);
end

G_Mpairwiseallnor=G_Mpairwiseall/sum(G_Mpairwiseall);

fgm=fgm+1;
GM_all(fgm,:)=G_Mpairwiseallnor;

for i=1:N
    fg=1;
    for j=1:n
        fg=fg*GM_all(j,i);
    end
    G_M(i)=power(fg,1/n);
end
G_meantotal=G_M';

ftx=fopen('xx.txt','w');

```

```

typef={'Administrator';'Staff';'Student'};

methodname={'***** The Rating method *****';'*****
The Ratio method *****';'***** The Point allocation
method *****';...
***** The Rank sum method
*****';'***** The Rank reciprocal method
*****';'***** The Rank exponent method *****';...
***** The Rank order centroid method
*****';'***** The Graphical method
*****';'***** The pairwise method *****'};

fgm=1;
kall=1;
for loop=1:n
    fprintf(ftx,'\r\n\r\n\r\n\r\n          %s',methodname{loop});

for kk=1:Nf

    fprintf(ftx,'\r\n\r\n\r\n\r\n
%s\r\n\r\n\r\n',typef{kk});
    fprintf(ftx,'      %12s %12s %12s %12s %12s
\r\n','CR1','CR2','CR3','CR4','CR5');
    fprintf(ftx,'-----
----- \r\n');

weight=mmt{kall};
ss=size(weight);

for k=1:ss(1)
    fprintf(ftx,'P%2d ',k);

for i=1:ss(2)
    fprintf(ftx,'      %5.4f ',weight(k,i));
end
fprintf(ftx,'\r\n\r\n');
end

fprintf(ftx,'-----
----- \r\n');

fprintf(ftx,'G_M ');
for i=1:5
    fprintf(ftx,'      %5.4f ', G_MM(kall,i));
end

fprintf(ftx,'\r\nG_Mnor');
for i=1:5
    fprintf(ftx,'      %5.4f ', G_MMnor(kall,i));
end
kall=kall+1;
end

fprintf(ftx,'\r\n\r\n\r\n\r\nG_Mnor_method');
for i=1:5

```

```

        fprintf(ftx, '          %4.3f ', GM_all(fgm,i));
    end

    fgm=fgm+1;

end

fprintf(ftx, '\r\n\r\n\r\nG_Mnor_Total');
for i=1:5
    fprintf(ftx, '          %4.3f ', G_meantotal(i));
end

fclose(ftx);

cr=1:5;
m1=GM_all(1,:);
m2=GM_all(2,:);
m3=GM_all(3,:);
m4=GM_all(4,:);
m5=GM_all(5,:);
m6=GM_all(6,:);
m7=GM_all(7,:);
m8=GM_all(8,:);
m9=GM_all(9,:);

Figure;
bar(m1);
axis([0 5 0 1]);
xlabel('Criteria (Cr)', 'FontSize', 12);
ylabel('Geometric Mean', 'FontSize', 12);
Figure;
bar(m2);
axis([0 5 0 1]);
xlabel('Criteria (Cr)', 'FontSize', 12);
ylabel('Geometric Mean', 'FontSize', 12);
Figure;
bar(m3);
axis([0 5 0 1]);
xlabel('Criteria (Cr)', 'FontSize', 12);
ylabel('Geometric Mean', 'FontSize', 12);
Figure;
bar(m3);
axis([0 5 0 1]);
xlabel('Criteria (Cr)', 'FontSize', 12);
ylabel('Geometric Mean', 'FontSize', 12);
Figure;
bar(m4);
axis([0 5 0 1]);
xlabel('Criteria (Cr)', 'FontSize', 12);
ylabel('Geometric Mean', 'FontSize', 12);
Figure;
bar(m5);
axis([0 5 0 1]);
xlabel('Criteria (Cr)', 'FontSize', 12);
ylabel('Geometric Mean', 'FontSize', 12);
Figure;
bar(m6);

```

```

axis([0 5 0 1]);
xlabel('Criteria (Cr)', 'FontSize', 12);
ylabel('Geometric Mean', 'FontSize', 12)
Figure;
bar(m7);
axis([0 5 0 1]);
xlabel('Criteria (Cr)', 'FontSize', 12);
ylabel('Geometric Mean', 'FontSize', 12)
Figure;
bar(m8);
axis([0 5 0 1]);
xlabel('Criteria (Cr)', 'FontSize', 12);
ylabel('Geometric Mean', 'FontSize', 12)
Figure;
bar(m9);
axis([0 5 0 1]);
xlabel('Criteria (Cr)', 'FontSize', 12);
ylabel('Geometric Mean', 'FontSize', 12)

```



Appendix H

MATLAB Program for TROI Method

```

function TROI_PROCEDURE_Code
global X N TROI pp res
N=input('Enter the matrix size');
TROI=ones(N,N);
X=ones(1,N);
A=1;
for ii=2:N
Element=input('Enter Element Troi');
TROI(1, ii)= Element;
TROI(ii,1)=1/ Element;
X(1,ii)= Element;
end
res=ones(1,N);
TROI
X
i=1;
pp=1;
[TROI,pp,res]=test(N,X,TROI,i,pp)
while pp>1
[rloc,rmax]=max(res(:,5))
X(1,res(round(rloc),1))=res(round(rloc),3)
X(1,res(round(rloc),2))=1/res(round(rloc),4)
TROI=ones(N,N);
TROI(1,:)=X;
TROI(:,1)=1./X;
TROI
res=ones(1,N);
pp=1;
[TROI,pp,res]=test22(N,X,TROI,i,pp)
end
TROI
end
function [TROI,pp,res]=test(N,X,TROI,i,pp)
res=ones(1,N);
for j=2:N-1
for w=j+1:N
if (X(i,j)>=1) && (X(i,w)>=1)
%disp('both int')
if X(i,j)>= X(i,w)
Z=abs(X(i,j)- X(i,w))+1;
k=w;
t=j;
TROI(k,t)=Z;
TROI(t,k)=1/Z;
else
Z=abs(X(i,j)-X(i,w))+1;
x=j;
y=w;
TROI(x,y)=Z;
TROI(y,x)=1/Z;
end
elseif (X(i,j)<1) && (X(i,w)<1)
%disp('both Fra')
S1=TROI(j,i);

```

```

        S2=TROI(w,i);
    if S1>=S2
        Z=abs(S1-S2)+1;
        c=j;
        d=w;
        TROI(c,d)=Z;
        TROI(d,c)=1/Z;
    else
        Z=abs(S1-S2)+1;
        b=w;
        h=j;
        TROI(b,h)=Z;
        TROI(h,b)=1/Z;
    end
elseif (X(i,j)>=1) && (X(i,w)<1)
    % disp('one int and one Fra')
    S=TROI(w,i);
    Z=TROI(i,j)+S;
    if Z>9
        E=Z-9
        temp2=TROI(w,i)-E;
        temp1=TROI(i,j)-E;
        res(pp,:)= [j,w,temp1,temp2,E];
        pp=pp+1;
    end
    zz=w;
    f=j;
    TROI(zz,f)=Z;
    TROI(f,zz)=1/Z;
else (X(i,j)<1) && (X(i,w)>=1)
    % disp('one int and one Fra')
    SS=TROI(j,i);
    Z=SS+TROI(i,w);
    if Z>9
        E=Z-9
        temp2=TROI(w,i)-E;
        temp1=TROI(i,j)-E;
        res(pp,:)= [j,w,temp1,temp2,E];
        pp=pp+1;
    end
    sm=j;
    mm=w;
    TROI(sm,mm)=Z;
    TROI(mm,sm)=1/Z;

end
end

end
res
end
function [TROI,pp,res]=test22(N,X,TROI,i,pp)
res=ones(1,N);
for j=2:N-1
    for w=j+1:N
        if (X(i,j)>=1) && (X(i,w)>=1)
            %disp('both int')
            if X(i,j)>= X(i,w)

```

```

        Z=abs(X(i,j)-X(i,w))+1;
        k=w;
        t=j;
        TROI(k,t)=Z;
        TROI(t,k)=1/Z;
    else
        Z=abs(X(i,j)-X(i,w))+1;
        x=j;
        y=w;
        TROI(x,y)=Z;
        TROI(y,x)=1/Z;
    end
elseif (X(i,j)<1) && (X(i,w)<1)
    %disp('both Fra')
    S1=TROI(j,i);
    S2=TROI(w,i);
    if S1>=S2
        Z=abs(S1-S2)+1;
        c=j;
        d=w;
        TROI(c,d)=Z;
        TROI(d,c)=1/Z;
    else
        Z=abs(S1-S2)+1;
        b=w;
        h=j;
        TROI(b,h)=Z;
        TROI(h,b)=1/Z;
    end
elseif (X(i,j)>=1) && (X(i,w)<1)
    % disp('one int and one Fra')
    S=TROI(w,i);
    Z=TROI(i,j)+S;
    if Z>9
        E=Z-9
        temp2=TROI(w,i)-E;
        temp1=TROI(i,j)-E;
        res(pp,:)= [j,w,temp1,temp2,E];
        pp=pp+1;
    end
    zz=w;
    f=j;
    TROI(zz,f)=Z;
    TROI(f,zz)=1/Z;

else (X(i,j)<1) && (X(i,w)>=1)
    % disp('one int and one Fra')
    SS=TROI(j,i);
    Z=SS+TROI(i,w);
    if Z>9
        E=Z-9
        temp2=TROI(w,i)-E;
        temp1=TROI(i,j)-E;
        res(pp,:)= [j,w,temp1,temp2,E];
        pp=pp+1;
    end
    sm=j;
    mm=w;
    TROI(sm,mm)=Z;

```

```

        TROI (mm, sm) = 1 / Z;

    end
end

end
TROI

end

```



Appendix I

Questionnaire for Validation of Final Results

Dear expert,

First, we should appreciate your kind willingness to give your general evaluation of our academic results.

The title of research: SELECTION OF THE BEST SUBJECTIVE CRITERIA WEIGHTING METHOD FOR EVALUATING E-LEARNING MODELS.

In this research we evaluated five major models of e-learning namely: 1) ICT supported traditional teaching, 2) flipped classroom, 3) blended learning, 4) synchronous learning and 5) asynchronous learning as the alternatives based on five factors (or criteria) about the e-learning implementation by using Multi-Criteria Decision-Making (MCDM) techniques.

We need your general opinion about the results of this research.

Result 1: Relative importance of criteria for e-learning implementation (see Table 1)

Result 2: Ranking of e-learning approaches to be implemented in a university (such as UUM) (see Table 2).

Table 1: Final Results for Criteria Weights about E-Learning Implementation

No.	Criteria	Relative importance	Rank
1	Human resources	0.265	2
2	Specific ICT infrastructure for e-learning	0.142	4
3	Basic ICT infrastructure for e-learning	0.135	5
4	Strategic readiness for e-learning implementation	0.276	1
5	Legal and formal readiness for e-learning implementation	0.182	3

Table 2: Final Results (Ranking) of E-Learning Approaches

Alternatives	Rank
Blended Learning	2
ICT supported Face-to-Face Learning	3
Flipped Classroom Learning	1
Synchronous Learning	4
Asynchronous Learning	5

INSTRUCTION:

A. Please tick (√) your level of **AGREEMENT** with the results based on the following scale

1
→
 7

Strongly disagree **strongly agree**

	1	2	3	4	5	6	7
Result 1	☐	☐	☐	☐	☐	☐	☐
Result 2	☐	☐	☐	☐	☐	☐	☐

B. Please tick (✓) your level of **CONFIDENCE** regarding your evaluation in part A based on the following scale

1  7

Strongly unconfident **strongly confident**

	1	2	3	4	5	6	7
Result 1	☐	☐	☐	☐	☐	☐	☐
Result 2	☐	☐	☐	☐	☐	☐	☐

We would be grateful if you could spare some time in completing this questionnaire.

Husam Jasim Mohammed

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