



Faculty of Cognitive Sciences and Human Development

**Job Candidates Filtering using Fuzzy Multiple Criteria Method for
Unskilled Occupations**

Tan Jia Kae

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Job Candidates Filtering using Fuzzy Multiple Criteria Method for Unskilled Occupations

Tan Jia Kae

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DECLARATION

I hereby declare that the work entitled “Job Candidates Filtering Using Fuzzy Multiple Criteria Method for Unskilled Occupations” is my original work. I have not copied from any other students’ work or from any other sources except where due reference or acknowledgement is made explicitly in the text, nor has any part been written for me by another person. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

Name of Student: Tan Jia Kae

Date: 4 May 2018

DEDICATION

This thesis is dedicated with deepest love to my family and friends.

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ABSTRACT

An e-recruitment system is the preferred choice for employers to recruit new workers. The challenges of any recruitment exercise are to specify the job-related and non-job-related requirements and employ those criteria for accurate filtering, ranking and selecting job applicants. In e-recruitment systems, one of the technical challenges is employing the specified job requirements to automate the candidate selection process. Using crisp rules to filter job candidates is too rigid and may miss good candidates. In this study, a framework which employs personal traits coupled with fuzzy logic method to rank job candidates for unskilled job positions in six different job sectors (construction, hotel, manufacturing, restaurant, sales and service) was proposed. The recruitment of unskilled workers is focused due to the high-turnover rate besides hardly-specified recruitment criteria. Furthermore, different employers might also have different sets of criteria in their selections. The contributions in this study are: (a) proposed the use of Kansei engineering approach to identify criteria that are most relevant to the selections of unskilled workers in different job sectors; (b) employed a fuzzy criteria framework that uses the job criteria identified to rank job candidates; (c) developed a web-based system that implements the proposed fuzzy multi-criteria ranking of job candidates. Searching from different sources has identified 50 useful personality traits to be formulated as Kansei words for candidate selections. Sixty (60) supervisors from six different job sectors have been interviewed and 20 traits which are most relevant to unskilled job have been selected. The F-TOPSIS method which implements the fuzzy multiple criteria decision-making using the 20 Kansei words to rank job candidates has also been employed. The results of the proposed system are compared with the ranking results of five experts from a company and the results obtained from the hamming distance

method. The results show that F-TOPSIS is a suitable solution to recommend and rank unskilled job seekers with high inter-raters correlation. In sum, this study proposes a complete framework of using Kansei engineering and F-TOPSIS method to build a recruitment selection system. The results show several key points: (a) Kansei engineering method is effective for the identification and selection of criteria for unskilled workers; (b) F-TOPSIS job candidates ranking has a high correlation with the ranking made by human experts; (c) fuzzy multiple-criteria approach offers a flexible way for recruiters to select and evaluate weightage for different criteria of a job advertised.

Keyword: FMCDM, F-TOPSIS, Kansei Engineering, Hamming Distance, E-Recruitment System.

Penapisan Pekerja Tidak Mahir dengan Menggunakan Kaedah Penilaian “Fuzzy” Pelbagai Kriteria

ABSTRAK

Sistem perekrutan dalam talian merupakan pilihan utama majikan untuk merekrut pekerja-pekerja yang baharu. Di antara cabaran-cabaran pembangunan sistem e-rekrutmen adalah menentukan kriteria pemilihan yang berkaitan dengan pekerjaan dan bukan pekerjaan serta bagaimana menggunakan kriteria untuk penapisan, menentukan kedudukan dan pemilihan pemohon kerja secara tepat. Dalam sistem e-rekrutmen, salah satu cabaran teknikal utama adalah menggunakan kriteria yang ditetapkan untuk mengautomasikan proses pengambilan pekerja. Penggunaan peraturan-peraturan dalam penapisan pemohon kerja adalah terlalu tegar dan mungkin akan terlepas pemohon yang layak. Dalam kajian ini, satu rangka kerja yang menggunakan ciri-ciri peribadi bersama dengan kaedah logik bagi menyusun kedudukan pemohon kerja untuk pekerjaan bukan profesional dalam enam sektor pekerjaan (pembinaan, hotel, pembuatan, restoran, penjualan dan perkhidmatan) telah dicadangkan. Pengambilan pekerja tidak mahir diberi tumpuan kerana kadar pusing ganti yang tinggi dan adalah sukar untuk menentukan kriteria pemilihan yang sesuai. Majikan-majikan juga mempunyai set kriteria pemilihan yang berbeza-beza dalam pemilihan pekerja. Sumbangan utama kajian ini adalah: (a) mencadangkan penggunaan kaedah kejuruteraan Kansei untuk menentukan kriteria yang bersesuaian dengan pemilihan pekerja tidak mahir dalam beberapa sektor pekerjaan; (b) menggunakan rangka kerja penilaian pelbagai kriteria berasaskan kaedah “fuzzy” dengan menggunakan kriteria pekerjaan yang telah ditentukan untuk menyusun kedudukan pemohon; (c) membangunkan sistem sesawang yang melaksanakan kaedah pelbagai jenis kriteria berdasarkan “fuzzy” dalam penyusunan kedudukan pemohon kerja. Hasil pencarian dari pelbagai sumber telah mengenal pasti 50 ciri-ciri personaliti

yang berkaitan untuk dirumuskan sebagai perkataan Kansei dalam pemilihan pekerja. Seramai enam puluh (60) penyelia dari enam sektor pekerjaan yang berbeza telah ditemuduga dan 20 perkataan Kansei yang paling sesuai dengan kajian ini telah dipilih. Seterusnya, kaedah “F-TOPSIS” menggunakan 20 perkataan Kansei tersebut untuk membuat penyusunan kedudukan pemohon-pemohon. Kaedah yang dibangunkan telah dibandingkan dengan lima pakar pengambilan pekerja daripada sebuah syarikat dan juga menggunakan kaedah “hamming distance”. Hasil perbandingan ini telah menunjukkan “F-TOPSIS” merupakan penyelesaian yang sesuai dalam mengesyorkan dan menyusun kedudukan para pekerja tidak mahir dengan korelasi antara penilai yang tinggi. Kesimpulannya, kajian ini mencadangkan rangka kerja yang lengkap dengan penggunaan kejuruteraan Kansei dan kaedah “F-TOPSIS” untuk membangunkan satu sistem perekrutan. Hasil kajian utama adalah: (a) Kaedah kejuruteraan Kansei adalah efektif dalam penentuan dan pemilihan kriteria untuk pekerja yang tidak profesional; (b) Penyusunan kedudukan pemohon kerja menggunakan “F-TOPSIS” mempunyai kadar korelasi yang tinggi dengan penyusunan dibuat oleh pakar sumber manusia; (c) Kaedah pelbagai kriteria berdasarkan “fuzzy” menawarkan cara yang fleksibel bagi para perekrut untuk memilih dan memberi keberatan kepada kriteria yang berbeza dalam pekerjaan yang diiklankan.

Kata kunci: FMCDM, F-TOPSIS, Kejuruteraan Kansei, Hamming Distance, Sistem E-rekrutmen.

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LIST OF ABBREVIATIONS

MCDM	Multiple Criteria Decision Making Method
FMCDM	Fuzzy Multiple Criteria Decision Making Method
HRM	Human Resource Management
KW	Kansei word
KE	Kansei Engineering
TOPSIS	Technique for Ordering Preference by Similarity to Ideal Solution
AHP	Analytic Hierarchical Process
ANP	Analytic Network Process
VIKOR	Visekriterijsko Kompromisno Rangiranje
ELECTRE	Elimination Et Choix Traduisant la REaite

CHAPTER 1

INTRODUCTION

1.0 Introduction

It is an undeniable fact that the expeditious evolution of latest information and communication technologies (ICT) has been devastating in recent decades. This fact is clearly shown especially since the first touchscreen smartphone was released in 2000 (Neuman, 2010). The rapid growing of ICT makes our daily lives be approaching towards the extremely aggrandised online information data at various categories in our shared digital environment. People have been progressively accessing to the web applications or client-server software applications through the internet in order to advance their knowledge and their skills. The main reason which people prefer using the web apps to get what they need is that online materials are easy to get on the internet, and most of them are free to be accessed and open sources (Ho, Kuo, & Lin, 2010). Other than that, looking for job offers through e-recruitment systems has been very popular amongst job hunters in developed or developing countries. The amount of job seekers who access the e-recruitment applications in JobStreets, LinkedIn and other job portals has been gradually increasing since 2012 (Faliagka, Tsakalidis, & Tzimas, 2012). Apart from job seekers, most companies also start using the online knowledge-based recruitment systems to seek for their employees or replacements. As intuitive as it gets, there are still challenges for effectively matching the requirements for both job hunters and employers in e-recruitment system because the matching criteria can be very subjective. Therefore, fuzzy multiple criteria method (FMCDM) becomes the most prevalent multi-criteria decision support method to solve the recruitment problems nowadays (Varmazyar & Nouri, 2014). This chapter mainly discusses

about the background of the study, the motivation of study, the problem statements, the research objective, the research questions, the definition of terms, and the significance of study.

1.1 Background of the Study

The internet, being developed in a breakneck speed, initiated the growth of the volume of accessible online information data in cyberspace. This directly increases the demand to multiply or expand the capability of internet users to accomplish all of their information (Al-Otaibi & Ykhlef, 2012). Not only this, it also inspires a great interest in technologies and precise research fields in order to achieve the wise management of this big data. These precise research fields include the information filtering and retrieving (Al-Otaibi & Ykhlef, 2012). A good information filtering can help user to automatically eradicate undesirable or unrequired information whereas a good information retrieval can retrieve the desired and required info during the matching processes (Hanani, Shapira, & Shoval, 2001).

Besides that, the advancement of ICT has transformed the ways organisations and recruitment agencies recruit employees. According to Ahmed, Tahir and Warsi (2015), the development of the internet has transformed the outdated and traditional techniques of recruitment methods into e-recruitments. The traditional methods used by companies are categorized in repeated, deliberate and costly procedures. Hence, recruitments through e-recruitment systems become the new trend in recruiting employee. This is manipulating the benefits of the World Wide Web (Faliagka et al., 2012).

E-recruitment is a process of using electronics which stand for identifying, attracting, and

selecting potential job applications from the online database for an employment (Lee , 2011). A E-recruitment benefits both human resource recruiters and job seekers because of its cost, effectiveness, time-savings characteristics and accessibility. Based on literature review on existing job recruitment systems, there are approximately 29 popular job portals in Southeast Asia. The large number of job portals clearly shows the e-recruitment systems have become the main recruitment channel in most of the organisations nowadays. Thus, it does not only become the new trend in recruitment techniques but also a popular choice for Human Resource Management (HRM) practitioners.

HRM is always the vital part on developments of any business companies (Varmazyar & Nouri, 2014). Choosing and tracking the candidates normally depend on different kinds of criteria, for instance, necessary skills, commitment to work, willingness for working duties, several of personality traits and etc. Therefore, multi criteria decision-making (MCDM) method becomes the superior scheme to hire a most advisable and adequate employee for a company. Meanwhile, implementing Fuzzy Multiple Criteria Decision-making (FMCDM) enables the recruitment systems to deal with the uncertainty and the ambiguity (Varmazyar & Nouri, 2014). In short, it is able to make recruitment systems receive the configuration of multi criteria selection problem of employers and employees.

In between HRM and the employees of a company, the recruitment is always the main phase in the long-term assurance (Florea, 2014). This is because it is the procedure of trying to discover and embolden potential job seekers to apply for an employment for the company. Employing a suitable applicant for a job offer is hypothetical to achieve high in a company. It is always the main concern of a company (Sarda, Sakaria, & Nair, 2014). It is principle to

be employed within the company. The employments with high quality are the consequences of the suitability between the applicants and the demands for the company. The key decision for the quality of the e-recruitments is based on candidate filtering and candidate ranking processes (Florea, 2014). Candidate ranking is the method to calculate and allocate scores for applicants (Faliagka et al., 2012).

Nevertheless, automated candidates job matching is a notoriously challenging task. It requires both filtering and ranking of applicants. Not only this, recruiters also need to identify the relevant criteria for the selections and once those are available, those criteria are to be weighted in terms of their importance in jobs. By giving the complications with the recruitment methods and processes, some of the human resource recruiters may choose external recruitment agencies by paying a huge amount of payments so as to get the best employees for the company (Florea, 2014). With the help of an external recruitment agency, human resource recruiters can simplify their complication processes in recruitment. Recruitment agencies can mark a very widespread of people at a slight cost. However, some of the small and medium sized (SME) businesses do not afford the cost.

Apart from that, most of the existing job portals normally apply only simple Boolean operations to compare the requirements for both employers and candidates. (Al-Otaibi & Ykhlef, 2012). However, this simplistic method returns many false hits. Based on the study by Ramar and Sivaram (2010) there was only 1 out of 120 candidates able to get chosen for a job advertisement. They concluded that the ratio of applications that succeeded to enter the interview sessions was only 1 out of 20 (Ramar & Sivaram, 2010). Hence, there were still many good and potential candidates failed to be selected into the interview sessions.

In addition, all recruitment systems are useful in recruiting employees but most of them are suffering from the divergences related with different and varying CVs formats and contextual information (Faliagka et al., 2012). Other than that, they are unable to get some important characteristics in order to do the evaluation processes. For instance, coherence and style are very vital for CV evaluations. Generally, most of the existing job portals use application tracking system (ATS) to track and screen the resumes and CV's of applicants, such as Monster and JobVite (Faliagka et al., 2012). When job seekers find the suitable job offer, they need to submit their resumes and their CV's to the system in order to apply for the job, then only they will be evaluated by HRM.

On the contrary, there is one job category which is unskilled job category that the resumes and the CV's are not necessary needed for them. Nevertheless, most of the existing job portals do not cover the unskilled job sectors. The reason is that the matching unskilled jobs to applicants is challenging as those selection criteria are hard to be specific in terms of professional qualifications. In facts, they are important as well as other job categories. Most of the temporary jobs and turnover-liked jobs need more employees. Therefore, this is one of the reasons for this research to be conducted.

In conclusion, an outstanding recruitment system should be able to enlarge its efficiency in filtering and recommending the best potential candidates for a job vacancy so that hiring of inappropriate individuals or missing out the good candidates can be avoided. The proposed system in this study is able to automate the unskilled job candidate filtering against the job offers' hiring requirements from employers by using FMCDM. Due to the process of recruitments depends too much on subjective properties, there are many uncertainty existing

within the job requirements, implementing fuzzy set theory, therefore, can handle variability problems occur on evaluations of job applicants, advance the effectiveness of judgements, and minimise subjective evaluations (Varmazyar & Nouri, 2014). From a different perspective, most of the people are fancy on using verbal expression to describe their feelings. Therefore, applying fuzzy linguistic technology into job recruitment evaluations is a better solution because it is able to translate the verbal expressions into numerical ones (Zadeh, 1965).

1.2 Motivation of the Study

Information Technology had transformed into a part of human daily lives. It helps people conduct work seamlessly. Most of the automated systems have been replacing manual labours significantly. For instance, electronic systems are able to keep tracks of any information changes in the vast database. More data can be analysed even when the data information increase. Next, the latest development in networking technology has built a network of people connecting globally for faster communications in a reduced time and cost. Examples of this technology include network social media and the e-recruitment systems.

Presently, some of the popular online job portals are JobStreets, Monster, JobDB and JenJobs. These job portals are still seeking for improvements for their job matching function to enhance the matching accuracy and relevancy between requirements for both job seekers and employers although they have been increasing their computation speed in servers. This is because they are still not perfect in job matching and candidate filtering.

Some of the factors like variety of jobs, different kind of job requirements from different job

sectors, resume-based evaluations and other special considerations in job matching make the job matching and candidate filtering in e-recruitment systems become a very challenging task. Screening job applicants normally depends on different kinds of criteria, such as necessary skills, commitment to work, willingness for the working task, several of personality traits, salaries, venues and etc. Therefore, MCDM method is a superior scheme to hire a most advisable and adequate employee for a company. Meanwhile, implementing FMCDM can deal with the uncertainty and the ambiguity properties (Varmazyar & Nouri, 2014).

Apart from that, most of the existing job portals do not cover the unskilled job category. The reason is that the selection criteria for unskilled workers can be so subjective that it is hard to be evaluated in terms of professional qualification. Consequently, this makes unskilled workers difficult to get job offers from e-recruitment systems. In short, doing research on evaluations of the unskilled job workers is a must in order to solve this phenomenon.

1.3 Problem Statement

Generally, most of the companies face recruiting obstacles ascending from acute working tasks, shortage of workers, competition for job applicants, workforce diversities and job turnovers (Lee , 2011). Turnover is the act of replacing the existing employee with a new worker. Hence, e-recruitment systems make a big impact on job searching and employee recruiting for both employers and job hunters. Due to technology advancement, competitions between organizations and limited labour markers, most of the companies have started to design their own recruitment systems on their websites. For instance, there is one navigation button to bring interested applicants to the web page for submissions of their resumes.

Although e-recruitment systems can make a cost reduction in transportation, paperwork, communication, and broadcasting of calls, much manual works are still needed to process the job applications. The recruitment systems are required to collect a lot of information concerning job seekers, such as resumes and CV's. This is because it is difficult to develop a well-defined uniform structure and a format which are enabled for the diffusion, the migration and the automation of analysing applicants' resumes.

Besides that, an excellent matching between job offers and job applicants based on multi criteria are difficult to evaluate. Most of the popular job portals are still improving their job matching features. This shows that the major truth for the area of personnel selection has not been extensively being implemented in recruitment systems. Therefore, the research on job matching is still an active research in the literature review. For instance, Md Saad, Ahmad, Abu and Jusoh (2014) implemented the fuzzy set theory in hamming distance method for personnel selection problems. Their proposed system is able to overcome some limitations in existing methods of MCDM like the inconsistency of judgements besides the increment of job candidates and criteria. Next, Keršulienė and Turskis (2016) used analytic hierarchy process method on job matching for the Chief Accountant Officer. Their proposed system is able to accomplish the data evaluation by using both linguistic and arithmetical measures. In addition, Baležentis, Baležentis, and Brauers (2012) employed the Fuzzy MULTIMOORA to do the job matching in order to improve the human resource recruitments. Their proposed solutions showed that the Fuzzy MULTIMOORA is suitable to deal with the business decision-making problems.

Currently, most of the recruitment systems undergo through an incorrect or an outdated

information retrieval technique (Al-Otaibi & Ykhlef, 2012). Due to its simplicity, most of those systems are still using these exact matching retrieval constraints in order to obtain the database search. They used queries consists of the amalgamation of keywords to perform the matching. This directly brings fault to a huge number of job applicants and make them lost the chance to be selected. For instance, JobMalaysia and JobStreets are using the traditional and simple rule-based approaches (Siraj et al., 2011). Boolean search technique is the most basic method to do the searching (Al-Otaibi & Ykhlef, 2012). Rule-based filtering is based on the if-else rule.

Furthermore, most Malaysians companies look for outsources like recruitment agencies if they need workers, especially unskilled workers. Hiring workers through recruitment agencies requires companies to pay more money in order to filter or screen out the better potential candidates for the job offered. Hence, providing an online recruitment platform for unskilled workers can reduce the cost in maintaining, updating and transaction of workers for most of the companies in Malaysia.

While e-recruitment systems, whose number is increasing every year, are becoming more important for graduate students, the sizes of unskilled labour is accounted for about 40% to 50% in 2009 of the labour markets in Malaysia (Tong, 2009). From there, the largest would be the service sector. However, the labour market which is always ignored and forgotten by the public is the non-professional workers or unskilled workers. They are mostly SPM leavers or those who do not own a cert. From the literature review on existing job portals, there are fewer than 18 out of 29 existing job portal websites in Southeast Asia that providing

the unskilled workers job categories, such as JobStreets, Monster, and MauKerja. This shows the ignorance of the need of unskilled workers in public.

On the other hands, it is hard to evaluate and judge the qualification and ability of work of unskilled workers to be matched to the job criteria as they do not have any proper certificates, resumes or CV's to submit. As compared to the skilled or professional workers, recruiters can evaluate and judge the ability of work of skilled workers based on the official certificates which are provided by skilled workers. It is necessary to have a solution to evaluate and judge the qualification of unskilled worker towards the job offers without judging unskilled worker based on official certificates. Therefore, the proposed system in this study implemented F-TOPSIS in order to automate the filtering and selection of unskilled worker based on multiple criteria in personality traits for each unskilled job offer without any official certificate. Nevertheless, unskilled occupations are important as well in recruitments and selections. Most of the temporary jobs and turnover jobs are considered as the unskilled occupations. For instance, part time promoters for some events or some roadshows. These part-time workers are only needed for a certain period which differs from the permanent jobs that the workers are needed for a longer period, ranging from 2 to 5 years. This has shown that there is a high turnover rate in unskilled occupations. The employers always need to recruit new unskilled workers once they have new events or roadshows during festivals.

Next, a large number of unskilled workers are needed by some unskilled sectors like manufacturing sectors and construction sectors. Apart from that, most of the employers in Malaysia choose to post posters or recruitment banners on their shops or the roadside billboards in order to recruit the unskilled workers. This is because they feel that it is no

worth of them to get unskilled candidates from the recruit agencies. Apart from this, some of the unskilled workers may not afford to access the internet for searching job online. However, traditional job recruitment method like only posting recruitment banner is outdated and inefficiency as it is hard to attract unskilled job seekers, and there are many free Wifi internet hotspot area for unskilled worker to use the internet such as shopping outlet, restaurant, and other free Wifi internet hotspots area, for instance, Majlis Bandaraya Johor Bahru in Johor, and Kuching International Airport in Sarawak. Therefore, it is necessary to include the unskilled jobs in job portals so that recruiting suitable job candidates in unskilled job sector is easier.

One of the methods to evaluate unskilled workers is based on the personality traits since they are related to the job performance. For example, the popular big five personality traits are amongst those which are commonly used as job candidate evaluation criteria. Caldwell and Burger (1998) had uncovered the evidence that there is linking relationship of big five personality traits to success in job interview. They targeted the applicants from business background who apply job positions such as sales promoter, sales marketing, and sales executives. Their result proved that there is positive correlation between big five personality traits and success in job interview. Thus, identifying the importance of personality traits can filter and rank the unskilled applicants. Due to multiple requirements in personality traits for a job position, FMCDM, thus, is needed. It can rank and filter the unskilled applicants based on the different fuzzy weight for each requirement. These criteria can be represented by identifying the Kansei words (KWs) from personality traits in Kansei Engineering (KE) model. Kansei Engineering (KE) is the technique that combines Kansei which stands for sensations, emotions and feelings by the engineering methodology (Shafieyoun & Maiocchi,

2014). Kansei Engineering (KE) is the technique that combines Kansei which stands for sensations, emotions and feelings by the engineering methodology (Shafieyoun & Maiocchi, 2014). It is an area which is conducted technologically in designing the products that are able to bring the contentment and happiness to user. By using KE model, it can calculate the preferred KWs from each unskilled job sector.

On the other hand, Human Resource Information System (HRIS) is software which able to support and help human resources (HR) experts or professionals with HR concerned tasks and functions, such as recording and managing organizations and employees' handbook (Harris, 2017). HRIS can save time and resources by achieving and completing HR related working duties more immediately and precisely (Masum, Beh, Azad, & Hoque, 2018). Unfortunately, conventional HRIS has some of limitations in solving the decision support problem when the problem is complex and unstructured (Masum, Beh, Azad, & Hoque, 2018). For instance, it is hard to gather the knowledge for knowledge-based system in HRIS when knowledge is informal, and it is difficult to verbalize and extract. Therefore, it is needed to implement the alternative artificial intelligence technique by using FMCDM in HRIS in order to solve the decision making problem.

In a nutshell, these are the reasons to implement FMCDM where the linguistic variables are defined from KE in the unskilled job candidate filtering and ranking.

1.4 Objective

The primary objective of this research is to propose FMCDM system for online recruitments and selections of unskilled workers.

1.4.1 Specific Objectives

The specific objectives are:

- i. To identify the prominent personality traits that are preferred by employers in different unskilled job categories in Malaysia.
- ii. To develop a framework for the recruitment selections by using personality traits and fuzzy system.

1.5 Research Questions

This study addresses several research questions as follows:

- i. What are the prominent Kansei words (KW) that are preferred by employers and recruiters in different kinds of unskilled sectors in Malaysia?
- ii. Is FMCDM where selection criteria are defined from KE suitable to filter and match the unskilled candidates in recruitment systems without the use of any resume, certificate and CV submission?

1.6 Significance of Study

This study mainly focus on unskilled job candidate filtering and ranking through FMCDM where the selection criteria are identified by using KE method. Thus, the present study contributes to unskilled worker evaluation method in job recruitments. The selection criteria which are analysed by statistical method can be used to filter and screen out potential job applicants. Besides that, the proposed system is able to automate the unskilled job candidate filtering and ranking. This is a benefit for unskilled job sectors.

1.7 Limitations of Study

The results presented in this study have demonstrated the effectiveness of FMCDM where selection criteria are defined from KE in unskilled recruitment systems. However, it only covers the big common and popular unskilled job sectors in Malaysia. They are construction, hotel, manufacturing, restaurant, sales and marketing, and service sectors.

1.8 Definition of Terms

1.8.1 Conceptual Definition

The conceptual definitions of some key terms used in this study are listed:

- i. E-recruitments are the processes of using electronics which stand for identifying, attracting, and selecting potential job applicants from the online database for an employment (Lee, 2011).
- ii. Boolean integrates the words, sentences or phrases that are keyed in by users, and limits, broadens and defines the query search (Al-Otaibi & Ykhlef, 2012).
- iii. FMCDM is the algorithm which integrates fuzzy set theory with multiple criteria decision making (MCDM) method (Dursun & Karsak, 2010).
- iv. F-AHP which stands for Fuzzy Analytic Hierarchical Process, is the mathematical methodology that uses the pair-wise comparison to access the relative importance of alternatives and criteria (Varmazyar & Nouri, 2014).
- v. A Technique of Order Preference by Similarity to Ideal Solution (TOPSIS) is Technique of Order Preference by Similarity to Ideal Solution (TOPSIS) is regarded to the instinctive norm which is preferred alternatively (Dursun & Karsak, 2010).

1.8.2 Operational Definition

The operational definitions of some key terms used in this study are listed:

- i. E-recruitments in the present study is known as the job portal which allows job seekers to find suitable job or recruiters to get the appropriate job candidates.
- ii. In this study, Boolean is explained as the data types that only has two possible values, true or false.
- iii. In this research, FMCDM is the artificial intelligence technique which integrates fuzzy set theory with multiple criteria decision making (MCDM) method.
- iv. In this study, F-AHP is known as the one of the FMCDM that uses the pair-wise comparison to access the relative importance of alternatives and criteria.
- v. A Technique of Order Preference by Similarity to Ideal Solution (TOPSIS) in this present research is explained as the core filtering engine in the proposed system.

1.9 Contributions

The contributions of this study are:

- i. To propose the use of Kansei engineering approach to identify criteria that are the most relevant for the selections of unskilled workers in different job sectors.
- ii. To employ a fuzzy criteria framework that uses the job criteria identified for job candidate ranking
- iii. To develop a web-based system that implementing the proposed fuzzy multi-criteria ranking of job candidates.

- iv. To propose an alternative AI technique that implementing the proposed fuzzy multi-criteria filtering technique which can be used in recruitment of Human Resource Information System (HRIS).

1.10 Conclusion

E-recruitment systems are the main recruitment platforms for most of the companies. However, there are still some limitations for the existing recruitment systems in Malaysia, such as the traditional and outdated filtering techniques and the ignorance of unskilled sectors in recruitments. Therefore, implementing FMCDM where selection criteria are defined by KE in job recruitments can solve the unskilled job candidate filtering and ranking problems. This chapter has discussed about the motivations and the problem statements to conduct this study. The following chapter inspects the related literature in order to conduct this study.

CHAPTER 2

LITERATURE REVIEW

2.0 Introduction

This chapter reviews past studies which are related to this study. Our review is focusing on the use of fuzzy multiple criteria method (FMCDM), where the selection criteria are defined by Kansei Engineering, for recruitments of unskilled occupations. The first section covers the occupational classifications. This section mainly concentrates on the job recruitment processes and job classifications in Malaysia. Next, the second section briefly describes on the Human Resource Information System (HRIS). Besides, the following section covers the filtering techniques used for job recruitment. Furthermore, the next section focuses on the Kansei Engineering (KE) Model. There is an explanation on how KE model can be implemented into this research. This section concentrates on personality traits that are needed for job recruitments. And, the last section focuses on the existing recruitment systems besides describing the strengths and weaknesses for each existing recruitment system in Southeast Asia.

2.1 Occupational Classification

Occupational classification is the method to show details related to kind of works which are executed in authorized, estate or a nation (Embury, 1997). This method can manage information about the job occupation and explanations methodically. Information of occupation classification are mainly applied for the group of people who requires to understand exactly the kind of works which are implicated in various type of occupations. For instance, the recruiters or trainers who want to give the correct guidance and professional

to job hunters, organize training activities for employees, and in-charged of job replacement. Even the knowledge of occupation classification about the occupation and explanations had designed priority to fit the requirements of users, it also needs to comprise the main requirement in order to apply for the corresponding formula or scheme (Embury, 1997). Hence, International Standard Classification of Occupation (ISCO) is designed to facilitate international communication of occupation information for both client-oriented and statistical users. It then becomes the national occupational classification scheme which is used by many of the countries.

Occupation classification includes two primary theories in ISCO. They are theory of the type of task performed, and the theory of skills (Ministry of Human Resource, 2010). Work or task performed can be described as a series of assignments and missions that are executed by a worker. Therefore, a series of works whose primary mission and assignments are similar are concerning to the same job (Embury, 1997). From the other perspective, employees and workers who execute the same duties and tasks are categorized in performing the same kind of occupation. Thus, they are categorised under the same job class without consideration of the responsibility of job experience and the degree of expedience (Ministry of Human Resource, 2010).

2.1.1 Skill Levels

Skill level is the ability of work model to label the job classification (Ministry of Human Resource, 2010). It is a scheme which identifies the scale and difficulty of the duties concerned. The difficulty of the duties has the precedence over the scale and ability specialization. According to Embury (1997), it reflects the kind of skill executed, tools and

equipment applied, and service produced. Therefore, skill level can be concluded as the capability needed to execute the certain assignment or mission of the working tasks.

Based on the study by Embury (1997), fundamental of the resemblance of ability needed to perform the work duties is the main key to determine the occupation classification. Therefore, public use skill levels to determine whether a people is competent to execute the work, and decides whether they are classified in the category. In fact, all job categories are determined based on the UNESCO's International Standard Classification of Education (Embury, 1997). Nevertheless, skilled level of a person cannot be concluded that it only can be gained by the proper education or formal training. It is because most of the skills that people obtained are from working experience and information training (Embury, 1997). Formal and proper training is more reliable, especially to some of the countries. It comparatively shows more significant to the high skill level occupations. Hence, occupation classification should be defined by the nature of ability to work but not the method for these skills obtained.

Apart from that, Malaysia classifies all of the jobs into three different categories, they are skilled occupation, semi-skilled occupation and the unskilled occupation (Ministry of Human Resource, 2010). Malaysia categorizes the jobs into these three groups depends on the Dictionary of Occupation Titles (D-O-T) to categorize the occupations into these three groups (Clain & Treiman, 1981).

2.1.2 Periodical

Periodical (D-O-T) is created by the United States Department of Labour (Clain & Treiman, 1981). This periodical help both the society and United Stated (U.S.) government to differentiate the kinds of occupation since 1983. Occupation analysts from U.S. government had visited thousands of workstation in order to inspect and cassette whole details of occupation (Clain & Treiman, 1981).

2.1.3 Skilled Workers

Skilled worker is the regimentation who needs to apply their judgement in decision-making (Ministry of Human Resource, 2010). They require to estimate, read, calculate, weight and judge during their work. This regimentation needs definite prerequisites and qualification such as education degrees or formal training. The reason is the workers need to use their intellectual reasoning and strong problem-solving capability for their tasks in work. Those professional trainings or workshops usually take at least six months to one year to master the skill for a work. Some of the occupations under this regimentation are doctor, nurse, lawyer, computer scientist, programmer, engineer, lecturer and other jobs that require a certificate to problem their qualification.

2.1.4 Semi-skilled Worker

Semi-skilled is the category that need to pay more attention on details or prevent from risks, however, they do not need to involve in complex working task (Ministry of Human Resource, 2010). Besides that, semi-skilled occupations do not need the worker to pass the superior professional training or academic like skilled occupation. They generally take three to six months for mastering the semi-skilled working tasks. Basically, they need to monitor,

check quality, and other repetitive works. Examples of semi-skilled occupation are security guard, waiter, clerk, sales promoter and other jobs that do not emphasize the certificate to prove their qualification and capability.

Based on the Ministry of Human Resource (2010), the unique requirements for semi-skilled work are summarised in Table 2.1.

Table 2.1: Unique requirements for semi-skilled work in Malaysia (Ministry of Human Resource, 2010).

Semi-skilled Job Category	Unique Requirements
Clerical Support Work	Workers need to know some basic skills on recording, organizing, storing and retrieving information associated to the duties in statistical, financial computing, and other arithmetic data, and executing other clerical tasks. For instances, operation of handling money, arrangement of travelling and assignment of appointments. All jobs of this category need the second level of skills (Ministry of Human Resource, 2010).
Services and Sales Work	Workers need to afford their private and shielding services concerning to housekeeping service, food and beverage, individual nurse, or prevent illegal actions. For instance, they act as models, and trade products in retail shop, stalls or markets. Thus, this category also needs the workers who have second skill level (Ministry of Human Resource, 2010).
Skilled Agricultural, Forestry and Fishery Work	Workers need to know some basic on growing and harvesting field and tree. They need to plant, yield and collect the nature fruits, plants strains, and sometimes they need to raise or hunt animals in order to product a variety of animal farming

Table 2.1 continued

	product. They need to have second level of skills for perform the duties (Ministry of Human Resource, 2010).
Craft and related trades work	Workers need to have some concrete epistemology and technical ability in the areas of construction, forming and erecting metal structures, maintaining and fixing machinery, fabrics, or timber. Basically, those tasks needs to be performed by handheld, and other tools which can reduce some physical strength and time required for the tasks. Occupations under this category requires the second level of skills (Ministry of Human Resource, 2010).
Plant and Machine-operators and assemblers work	Workers need to know to manipulate and investigate industrial, geoponic mechanism and tools, steer and control trains, engine vehicles or congregate goods from element sections. Normally, their duties need some experiences with comprehensive of manufacturing and geoponic. They also need the second level of skills (Ministry of Human Resource, 2010).

2.1.5 Unskilled Worker

Unskilled worker is the group which performs only for simple task (Ministry of Human Resource, 2010). This simple task does not require the unskilled worker to train their judgement skills. Comparing with skilled and semi-skilled occupation, time needed for cramming their skill is the shortest. According to Ministry of Human Resource (2010), they normally take one month or less to completely gain the ability for the works. However, some of the unskilled jobs have the significant different requirements which they need to have strong physical strength or coordination. This is because those tasks require the worker to perform by using their physical strength. Examples of this group are cleaner, food stall

helper, messenger, operator, flyer distributor and other works that might need the physical strength to perform with.

Based on Ministry of Human Resource (2010), the unique requirements for unskilled work are epitomized in Table 2.2.

Table 2.2: Unique requirements for unskilled work in Malaysia adapted from Ministry of Human Resource (2010).

Unskilled Job Category	Unique Requirements
Elementary Occupation	Workers needs to execute simple and repetitive works or duties which mainly need workers to use of equipment and strong physical energy. Most of the jobs under this group require the first level of skills (Ministry of Human Resource, 2010)

2.1.6 Skill Specialization

Skill specialization is the term to describe technical ability of worker in term of area of knowledge needed, instruments and installation used, and product generated (Ministry of Human Resource, 2010). Generally, this is the function to specific knowledge, tools or materials needed for certain working tasks and performance of the duties.

In Malaysia, classification of occupation is based on Malaysia Standard Classification of Occupation 2008 (MASCO-08). It is domestic standard for jobs that regarding to redirect the job configuration and local employment (Ministry of Human Resource, 2010). MASCO-08 was established according to ISCO by International Labour Organization. Thus, occupation classification in Malaysia is based on skill level and skill specialization.

There are four main skill levels which are categorized based on education level. They are epitomized in Table 2.3.

Table 2.3: Skill levels based on education level in Malaysia adapted from Ministry of Human Resource (2010)

Skill Levels	Education Level	Major Group
First (unskilled category)	Primary Education	Elementary Occupation
Second (semi-skilled category)	▪ Secondary or post-secondary education ▪ Malaysian Skills Certificate (SKM) Level 1 -3	▪ Clerical Support Staff ▪ Serving and Sales Labours ▪ Proficient Farming, Forestry and Fishery Labours ▪ Craft and Related Skills Labours ▪ Plant and Instrument-manipulator and Assemblers
Third (skilled category)	▪ Third Tertiary education leading to an award not equivalent to a first University Level ▪ Malaysian Skill Certificate (SKM) Level 4 or Malaysian Skills Diploma (DKM) Level 4	▪ Technicians ▪ Associate Professionals
Fourth (skilled category)	• Tertiary education leading to a University or postgraduate university degree • Malaysian Skills Advanced Diploma (DLKM) Level 5-8	▪ Professional

From Table 2.3, it shows clearly that in Malaysia, jobs are classified into four main categories based on education level. Major jobs are also listed accordingly to the education level. In a nutshell, the semi-skilled workers need to have at least secondary, post-secondary

education or SKM from level 1 to 3. There are distinct and unique requirements from this semi-skilled work. Different sectors have distinct requirements which are listed in Table 2.1. On the other hand, unskilled group only needs to have first skill level which the workers can get the skill from primary education. Nevertheless, the workers need to be physical strong and fit in body size. It is because most of the unskilled worker requires the considerable physical effort to perform the tasks.

2.2 Human Resource Information System (HRIS)

Human Resource Information System (HRIS) is software which able to support and help human resources (HR) experts or professionals with HR concerned tasks and functions, such as recording and managing organizations and employees' handbook (Harris, 2017). HRIS is the computerized information system consisting of a set of database which enable the HR professionals to enter, store and manipulate the employees' data of an organization (Rao & Dhillon, 2017). HRIS is an essential equipment for HR professionals to attain the competitive advantages in organization (Masum, Beh, Azad, & Hoque, 2018). Thus, HRIS can be concluded it is an application that makes use of information technology for HR professionals to handle the HR related working duties. The example of HR functions are gathering, keeping, sustaining, and restoring data which is indispensable for an organization, such as safety techniques, emergency evacuations and employee's handbooks (Rao & Dhillon, 2017).

Nowadays, HRIS works as vital part in decision making process in HRM. Although HRIS is not the new notion in HRM, it is still improving with dynamic business models in each of the organization (Rao & Dhillon, 2017). The increasing demand of HRIS shows the

acceptance and admission of the HR professionals that information technology should be implemented in HR related functions (Rao & Dhillon, 2017). HRIS can save time and resources by achieving and completing HR related working duties more immediately and precisely (Masum, Beh, Azad, & Hoque, 2018). Besides, HRIS is very useful to store large data because it consists of database. It helps organization to retain a precise, intact, updated data which stored in database, and these data can be recovered from documents, such as manuals and reports (Rao & Dhillon, 2017). Therefore, HRIS is very helpful in HR functions in any organizations.

With the conformation of more intricate HR functions which concentrated on organization's performance goal, HRIS have developed into more advance expert system which included analytic tools in order to sustain the decision making in administrative human resources (Rao & Dhillon, 2017). Due to the requirement of HRIS to solve the decision making problem in HRM, implementing a set of Artificial Intelligence (AI) technique, for instance Knowledge-based reasoning and machine learning is able to solve the decision making problem more precise in HRIS. Based on Masum, Beh, Azad, and Hoque (2018), implementing AI technology in HRIS able to get superior information and knowledge from past experience and data to sustain the decision making problem. Basically, HRIS handles all the HR related functions, they are performance assessment, recruitment of new employee, personal self services, leave and absense, payroll, employee managing, compensation, and development of employee (Rao & Dhillon, 2017). The main focus of this study is the recruitment of new employee.

For the recruitment function in HRIS, it allows HR professionals and HR managers to

determine and evaluate the recruitment process that implemented in the organization. HR professionals and HR managers can identify the new applications, handling and filtering the incoming applications, communicating with applicants, and evaluate and hire the selected applicants in the HRIS. Generally, HRIS consists of three main functional components, they are input subsystem, HRIS database, and output subsystem (Rao & Dhillon, 2017). The input subsystem acts as the first stage of HRIS. It includes all data processing processes, such as HR research and HR intelligence. Next, the HRIS databases can gather all the data and information from the input subsystem, and store them in the computer storage, for instance, Database Management system (DBMS) is used to create database tables, store information in databases, and maintenance and update the database in HRIS (Masum, Beh, Azad, & Hoque, 2018). Moreover, the output subsystem is in charge of all the output result based on the specific HR functions, such as getting the selected new applicants or candidate in the recruitment. Thus, with these three vital components, HRIS able to assist HR professional to replace the manual works in gathering, saving, maintaining, sustaining and retaining required and related information and data effectively with the growth of an organization. and

The previous study of HRIS highlighted the HR functions by implementing HRIS in organization. Shiri (2012) stated that HRIS helps HR professionals to generate more effective consequent than traditional manual works which can be done on papers. It is because HRIS can retrieve any kind of previous data and information that had stored in database. Shiri (2012) also suggested that HRIS do not only limited to work in simple administration works but overall of HR functions that can save time and resources of an organization. Besides, Kundu and Kadian (2012) discovered that HRIS is regularly applied in employee records and pay sheet actions. For instance, employee's performance and

reward management, and technical and strategy of HRM are the most rapid and common functions that used by HR professionals in HRIS (Kundu & Kadian, 2012). Moreover, Singh, 2017) find out that there is strong linkage relationship between HRIS and recruitment. HRIS can improve and support the recruitment process of an organization (Singh, 2017). For instance, HRIS provides the job application forms, psychometric testing for certain job position, assessment, and intelligence quotient. It is easy for HR professional to filter the potential candidates based on the result from the assessment and testing which provide by HRIS.

2.3 Job Recruitment Process

Recruitment is the main purpose of forming HRM in a company. According to Färber, Weitzel and Keim (2003), HRM needs to treat the employees as the most vital resource of production. From a different perspective, job recruitment process is the process to attract and find the potential candidates from a group of applicants. The main concern of a job recruitment process is to employ job seekers who fit the requirements of a job position. Basically, job recruiter posts a job advertisement which includes specifying the job prerequisites and restricts on technical ability, and other specific qualifications. Then, job hunters need to prove their qualification and skills by providing the resumes, cover letter (CV), or certificates (Fazel-Zarandi, 2009). However, for the unskilled workers, they have no formal qualification with certificate. Neither they have resume or professional training. . Therefore, it is hard to evaluate and judge the unskilled job seekers whether they are matched to a job offer criteria.

Based on the study of Färber et al. (2003), the standard recruitment procedure can be

compartmentalized into two major stages. They are attraction stage and selection stage (Färber et al., 2003). The similarity of these two processes is they need to undergo the planning and execution sections. The planning section decides the whole strategy to fascinate the potential job seekers as well as to accurately filter and select from the pool of candidate job applicants. It (Al-Otaibi & Ykhlef, 2012). Therefore, selection strategy must be formulated at this state. The execution section consists of recruiter branding actions such as marketing strategy to fascinate eligible job seekers (Färber et al., 2003). On the other hand, the selection process comprises the pre-screening of submitted resume or CVs, and final selection to compare the remaining potential job seekers (Al-Otaibi & Ykhlef, 2012). Most of the recruitment processes begin with pre-screening of resumes, CVs and certificates. After that contrasting between those applicants who passed the pre-screening section occurs. Hence, it is hard for those unskilled workers to be selected through the pre-screening process because they do not have a proper resume, CV, and certificate. This shows that we cannot use the same evaluation method by professional skilled worker for unskilled worker. Figure 2.1 shows the recruitment process which is adapted from Lang, Laumer, Maier, and Eckhardt (2011).



Figure 2.1: Recruitment process (Lang et al., 2011).

2.4 E-recruitment System

E-recruitment system is the platform of using electronic which stands for identifying, attracting, and selecting potential job applicants from the online database for an employment (Lee, 2011). In general, e-recruitment system indicates the source of job online which

included job advertisement, submitting resumes or CVs, and compiling database of human resource (Mat Zin, Jaafar, Mat, Alias, & Ashari, 2016). There are plenty of e-recruitment activities especially for job advertisement posting, for instance those appear on online recruitment systems or companies' websites, accepting job applications on the internet, and screening application (Singh & Narang, 2008). E-recruitment system can attract huge number of potential job hunters at once because of the accessibility and convenient brought by the internet. The internet and web-technology become enabler that totally changed recruitment strategy, from the employers to job hunter's screening (Bussler & Davis, 2002). The traditional recruitment method is time consuming with restricted in size of geographic reach and high cost. E-recruitment system offers global coverage and speed because internet can provide outstanding communication function as long as the user is connected to internet. Therefore, most of the recruiters start relying on e-recruitment system. Since the late of 1990s, the E-recruitment platform has gained popularity due to the speedy growth of economy which requires many eligible workers (Al-Otaibi & Ykhlef, 2012). Based on the study by Smith and Rupp (2004), an approximation of one out of four job hunters use e-recruitment system to search for job vacancies.

There are numerous of benefits to take advantage of e-recruitment system. The most distinct benefit would assuredly be the cost and time savings to the recruiters (Kim & O'Connor, 2009). The length of the time needed for the complete recruitment is reduced (Mat Zin et al., 2016). For example, the conventional recruitment solution such as posting job advertisement on newspaper may take from a day to months to get the suitable job seeker but the job hunters can give immediate action or response if job hunter come across it through e-recruitment system. Using e-recruitment system is 70 percent faster than conventional

hiring solution at every recruitment step from posting job advertisement, getting submitted resumes or CVs, and screening the candidates (Kaur, 2015). Shorten recruiting time can directly make an impact on recruiter as recruiter is easy to identify job applicants who had applied previously, and create consistency the recruitment process such as standardizing the resume templates. Meanwhile, the cost of job posting on e-recruitment system is usually lower than job post on printed media like newspaper, and recruitment agencies (Malinowski, Keim, & Weitzel, 2005) templates. E-recruitment system can minimize firm's dependence and costs on recruitment agencies because recruiters can automatically post job advertisements onto their own branded website or external job portal to increase the awareness by fascinating job seekers to apply.

Moreover, Allden and Harris (2013) said that burden of human resource and costs for recruitment in the organization are significantly subsided after using e-recruitment system. The corporate information systems being integrated by tools can make some tasks of e-recruitment systems be automated, causing the e-recruitment systems to be able to diminish loads of human resource. For instance, once job seeker submits job application through e-recruitment system, recruiter automatically receives the job application notification from the email.

In addition, e-recruitment system can reach of passive job hunters (Hays, 1999). Passive job hunters are the group of job seekers who do not actively search for job, but they are still interested in getting a job with higher working quality, such as higher wages or newer working experience. According to Kinder (2000), passive job seekers express a trend among today's workforce like high turnover rate in every occupation, they are more variable, having

specific knowledge and less affiliated to companies. Hence, based on numerous of advantages of e-recruitment system, it can be concluded that it becomes the solid part of the recruitment solution.

E-recruitment systems are mostly presented in web application such as JobStreets (<https://www.jobstreet.com.my/>), Monster (<https://www.monster.com/>) and CareerJet (<https://www.careerjet.com/>). However, most of recruitment systems encounter from inappropriateness of Boolean search technique to find the potential job applicants (Al-Otaibi & Ykhlef, 2012). Boolean search is built on a technique of symbolic logic which is developed by George Boole (Tomaszewski, 2015). George Boole proposed three Boolean operators, AND, OR, NOT, and he used these three Boolean operators to compare of mathematical function (Tomaszewski, 2015). Generally, Boolean search is basic a search technique that can be used when searching online database and web search query. For instance, many search engine and online databases carry out search function with these three Boolean operators, and directly compares with the keywords terms which can be in term of string text, numerical or combination of search string and numerical terms (Tomaszewski, 2015).

Boolean search in e-recruitment system uses search queries which consists of combination of keywords to identify the selection criteria in order to match the job seeker (Färber, Weitzel, & Keim, 2003). Nevertheless, this elementary and basic technique is not sufficient to match the complex job seeker's profile to the requirements of a job (Malinowski, Keim, Wendt, & Weitzel, 2006). There may be many false positives in the result set, for instance, under qualification job applicants exactly match the search criteria (Singh, Rose,

Visweswariah, Chenthamarakshan, & Kambhatla, 2010). One example is given by Al-Otaibi and Ykhlef (2012): A job has seven criteria which are minimum MSc, minimum BSc, software engineering, computer programming or information technology related field, has previous experience, experience more than four years, English skill level good, and owns Oracle developer certificate. For each candidate, the score assigned to each criterion is either 1 (true and exist) or 0 (false and not exist).

The recruiter aims for the candidate who has the score of [0 1 1 1 1 1 1]. There are five candidates apply for the position: (a) person A with the score of [0 0 1 0 0 1 1], (b) person B with the score of [0 1 0 1 1 1 0], (c) person C with the score of [0 1 1 1 1 1 0], (d) person D with the score of [0 1 0 1 1 1 0], and (e) person E with the score of [1 1 0 1 1 1 0]. From here, none of the candidates is chosen for the position. This shows that Boolean search is insufficient in recommend the best and quality candidate in this situation because Boolean search will return all the candidates who have exactly same results from the keywords from recruiters. This directly shows ignorance and difficulty in presenting the ratings of each candidate in Boolean search. Apart from Boolean search, person C is chosen and considered as the best candidate if implementing the Euclidean distance to calculate the similarity measure between job requirements and candidate (Al-Otaibi & Ykhlef, 2012).

Figure 2.2 shows the comparison of traditional recruitment process and the e-recruitment system which is adapted from Holm (2012). It shows clearly the whole processes of traditional recruitment process which are mainly depends on recognizing and recruitment candidate in linear diagram. Next, Figure 2.3 shows the integrated architecture for candidate filtering component in job recruitment system which is adapted from Laumer and Eckhardt

(2009). The integrated architecture of e-recruitment system (Laumer & Eckhardt, 2009) is an extended edition of architecture of e-recruitment system from Lee (2007) by integrating job recommender and job profiles subsystem. Conforming these two additional subsystems to support the development of job profiles and automated recommendation solution.

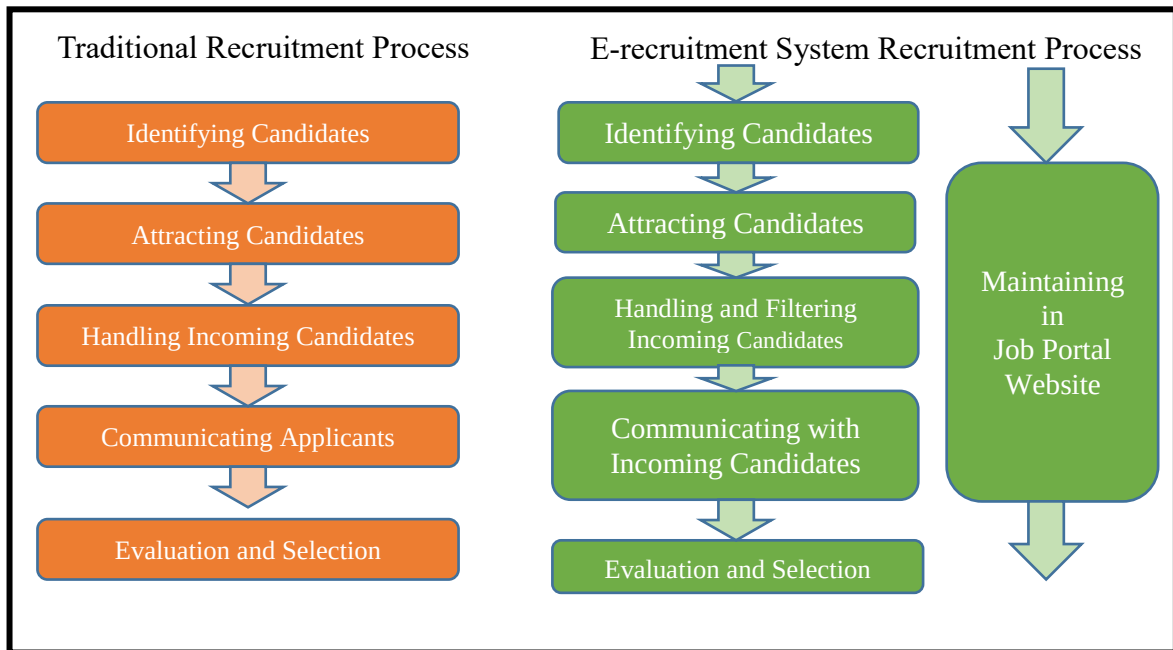


Figure 2.2: The comparison of traditional recruitment process and the e-recruitment system adapted from Holm (2012).

Lee (2007) proposed architecture of e-recruitment system, workflow management subsystem works with database management subsystems, and functions as the central component for the whole e-recruitment system. The main purpose of the database management subsystem is to store all data like job profiles, job advertisement, and job application. Workflow management subsystem works as intermediated subsystem because it supports the entire e-recruitment processes. For instance, after job seeker entered his or her job profiles, and uploaded resumes or CVs, workflow management subsystem will trigger the applicant tracking subsystem to filter the potential applicants.

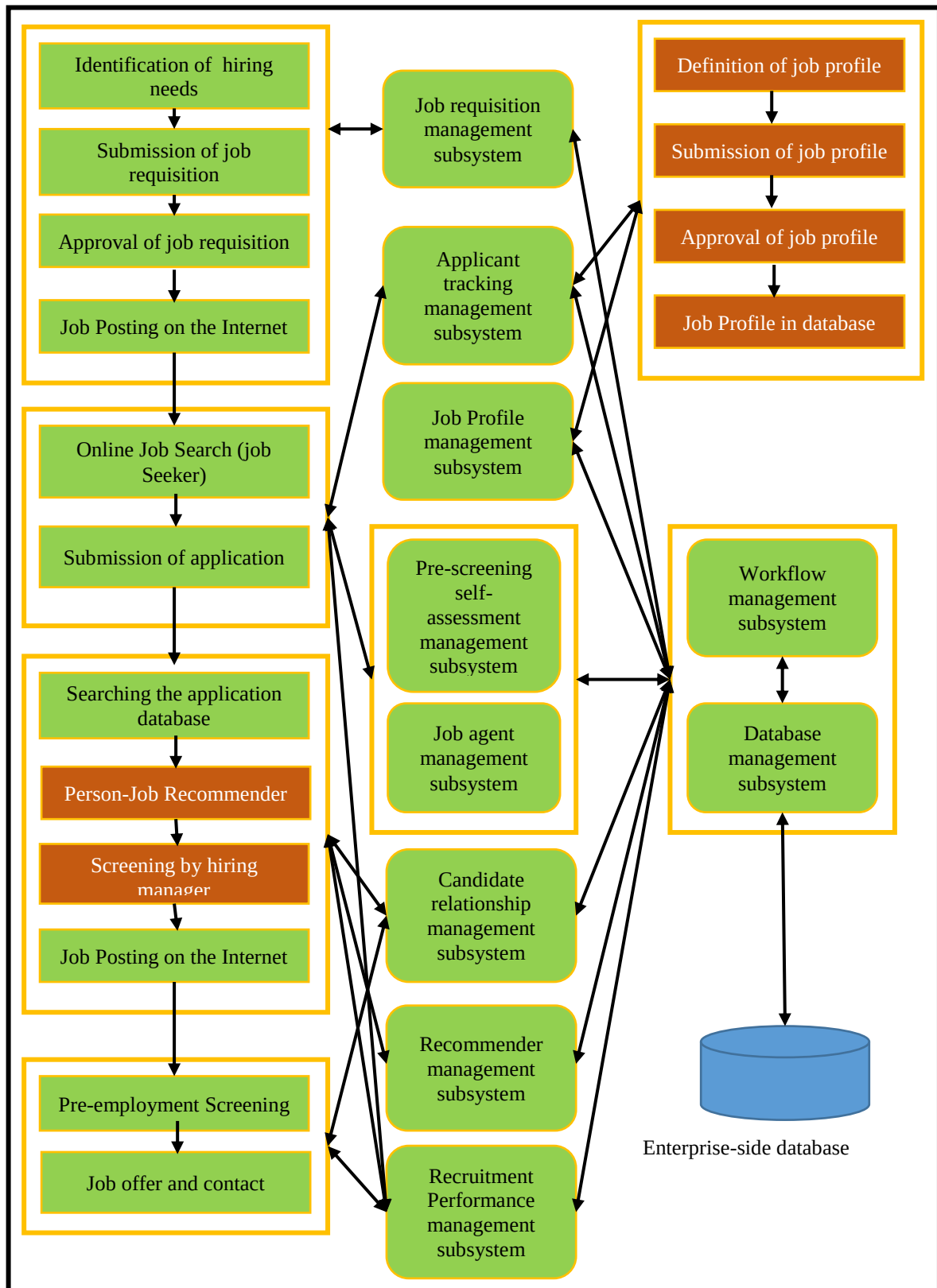


Figure 2.3: The integrated architecture for candidate filtering component in job recruitment system which is adapted from Laumer and Eckhardt (2009).

Laumer and Eckhardt (2009) proposed job profile management and job recommender subsystems in addition to part of e-recruitment sub-system of Lee (2007). Generally, job profile plays vital role in an e-recruitment system. As analysed by Smits, McLean, and Tanner (1993), job profile is the fundamental key to effectively fascinate of job seeker. Job profile subsystem requires recruiter to define clearly the selection criteria for each of the job vacancies (Laumer & Eckhardt, 2009). For example, recruiter or human resource manager needs to define the requirements or lists of require skills that the job applicants must have.

Recommender subsystem works as recommender in selection phrase of the recruitment process. It can decide the qualification of a job applicant, and recommend the job applicant to recruiters if he or she is qualified for the job (Laumer & Eckhardt, 2009). For instance, job applicant who has BSC in Computer Science is automatically matched to the job profiles of the recruiter who needs to hire the computer programmer who at least owns the BSC degree in related field.

There are few e-recruitment systems have been integrating both recommender system and classical information retrieval method in candidate screening and filtering.

E-Gen system is an automated processing of job offer system for HRM (Kessler, Torres-Moreno, & El-Bèze, 2007). It consists of two main components: (a) job profile categorization; (b) job candidate recommender. Job Profile categorization works as the classification scheme. This classification scheme needs to categorize the job postings directly from email with attached documents of recruiters, which are written in unstructured format with some errors and ambiguities. E-Gen system analyzes the email, and parses the

attached documents by splitting the document into few segments. The splitting segments which contain the extracted text contents are assigned to a relevant label by using Support Vector Machine (SVM) in primary region of the categorization of the word in the job offers (Kessler et al., 2007). The extracted text contents are the keywords from the documents, such as five years of working experiences in resume.

E-Gen system employs LibSVM library (Fan, Chen, & Lin, 2005) to perform the multi-classes problem in job recruitment. Multi-class is the label that assigned by SVM, such as job titles, description of company, requirements of job posting and job application profiles (Kessler et al., 2007). Moreover, it improved the SVM score as decreasing in mean square error which stands for the incorrect classification of job offers by using the counteractive method (Kessler et al., 2007). From the architecture of E-Gen can be concluded that it is a self-regulating and moveable database system because it takes email as input whereas the XML files as output. It can execute and classify the formless job advertisements (Kessler et al., 2007). It can also investigate and rank the job applicants.

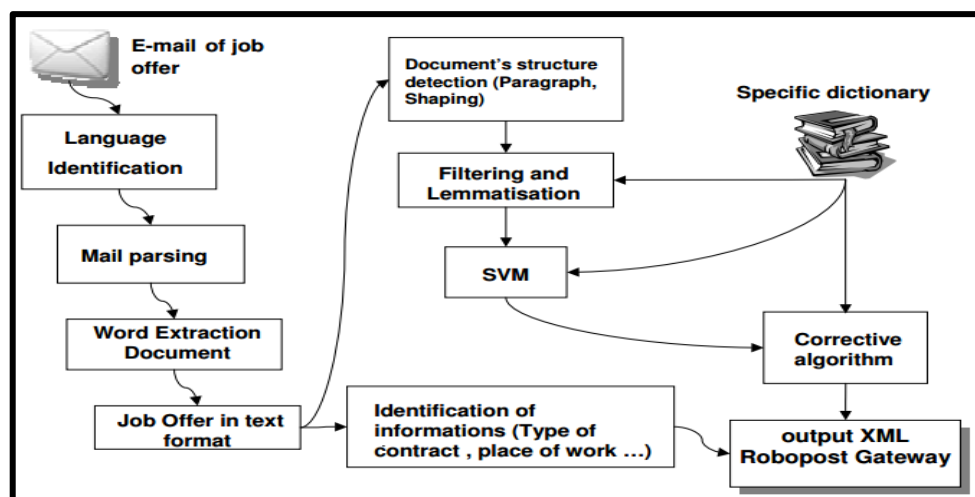


Figure 2.4: The Architecture of E-Gen System (Kessler et al., 2007).

Competency Management through Ontologies (CommOn) framework (Radevski & Trichet, 2006) is another example of e-recruitment system that has been proposed for candidate screening and filtering. It is developed based on three components: (a) competency reference system, (b) competency profiles, and (c) automated matching profiles. Competency reference system provides all the information about the specific job sectors like healthcare, banking and financial. The information about each job sector includes knowledge about the job sector, skill about the task and aptitude. On the other hand, competency profiles includes all the data related to job hunters, job postings and job requirements. Radevski and Trichet (2006) said that competency profile is mainly focused on behavior aptitudes such as the evaluation of personality traits from answers to questions, and define the behavior aptitudes for each job seeker based on the result of the questionnaire. The automated matching profile works as bridge to match the both job offers to the suitable job seeker based on the competency reference system and competency profile.

Knowledge-based system is constructed based on these three main components of CommOn framework by semantic web method. Semantic web is an extension of basic HTML webpage with machine-readable information (Bizer et al., 2005). Based on study by Berners-Lee, Hendler and Lassila (2001), semantic web is also one of the knowledge representation method that enable computer machine to understand the structure collection of information and sets of inference rules which mainly used in semantic matching for automated reasoning in knowledge-based system. Semantic matching is the method of automated matching based on the inference rules and reasoning in knowledge-based system (Berners-Lee et al., 2001). By implementing the semantic web method, CommOn can classify job offers in xml format that HR-XML can sustain the label stified (Radevski & Trichet, 2006). CommOn framework

requires job hunters to answer online questionnaire during signing in section in order to collect the personality traits of job seekers for requirements. However, this strongly affects the user friendliness of the system because the process of applying a job becomes time consuming (Faliagka et al., 2012).

Faliagka et al. (2012) proposed an e-recruitment system that implements analytical hierarchy analysis (AHP) algorithm to do the automation of candidate ranking. Candidate ranking process is based on the relative weight of each selection criterion which is key in by employers. For example, the recruiter needs to define the weight for each selection criterion of specific job postings. Two main components of this proposed system by Faliagka et al. (2012) are personality mining and job applicant ranking. For personality mining, job seeker requires to log into the system through LinkedIn account, and this enables the automated extraction of relevant criteria for pre-screening of job seeker, directly from the LinkedIn profile. Faliagka et al. (2012) used text analysis method which is Linguistic Inquiry and Word Count (LIWC) to extract the linguistic feature which acts as label of candidates' personality trait.

LIWC is one of the text analysis tools that are able to analyze the text data by calculating the relative frequencies of words that fall in each text category, such as the number of text "happy" appears in the whole blog of candidates. For application ranking, AHP plays an important role in automated candidate ranking. AHP is another multi-criteria decision-making method. AHP uses multi-level of hierarchical structure to calculate weight for each different selection criteria of a candidate, based on the requirement and weight of job posting

(Faliagka et al., 2012). Therefore, based on study of Faliagka et al. (2012), their proposed system by using AHP was engaged in huge scope of recruiting scenario.

EXPERT is another example of e-recruitment system that proposed by Senthil Kumaran and Sankar (2013). EXPERT implements ontology mapping in automated candidate screening in order to recommend the best candidate. There are three recruitment phrase in EXPERT. The first phrase is collection of job applicant's resume. Meanwhile, the ontology for relevant feature is constructed from the attached resume. The second phrase is to collect job requirements which are represented as another ontology. The last phrase is to map the first ontology from resume onto the second ontology by using ontology mapping, and screening out the best job applicant. Ontology mapping is also known as semantic matching (Senthil Kumaran & Sankar, 2013). Ontology mapping is the process of knowledge sharing in an environment with different ontologies. Generally, ontology mapping is the process of mapping an ontology onto one or more, where each node is mapped to all the other nodes that are semantically equal (Senthil Kumaran & Sankar, 2013).

Salazar, Jaramillo, Ovalle, and Guzmán (2015) proposed an e-recruitment system which able to do candidate screening and ranking. They implement the case-based multi-agent system (MAS), and integrate the ontology mapping in order to recommend and rank the candidate. The MAS includes three main components, they are inference rules, case-based reasoning and similarity percentage (Salazar, Jaramillo et al., 2015). The inference rules are developed by using production rule. The production rule is used to adapt the job hunters to the job requirement. For example, job offer X has qualification of Y and competency name of Z whereas the job seeker A has qualification of B and competency name of C, if the

qualification of Y is equal to qualification of B, and competency name of Z is equal to competency name of C, then the job seeker A has the chance to be selected. For the case-based reasoning, it works as the knowledge database that store all the previous success cases, and represented as instance within the same ontology. For similarity percentage, it uses to calculate the ranking for each applicants. Based on the study by Salazar et al. (2015), the higher the similarity percentage toward the previous success cases in case-based reasoning, the higher chance of the applicant to be selected.

2.5 Job Candidates Selection

It is an unquestionable fact that many employers are not getting the right workers, and employees have taken the occupation which do not fit them. The main reason is the requirements of occupation changed dramatically (Wille, De Fruyt, & Marjolien, 2010). Apart from that, unskilled workers cannot be evaluated by the same evaluation method which is used by skilled worker in terms of job performance and job recruitment. The selection criteria for unskilled workers can be very subjective, and difficult to specify in term of professional qualification. For example, skilled professions have certificated qualifications, resumes while those are not necessary needed for most of the unskilled workers. One of the methods to evaluate unskilled job candidates is based on the personality traits since they are related to job performance. For example, the Big Five Personality Model are amongst that are commonly used as job candidate evaluation method criteria. Therefore, identify the importance of personality traits can filter and rank the unskilled application in job recruitment.

2.5.1 Big Five Personality Trait Model

The Big Five Personality Trait Model had been proposed by Barrick and Mount (1991). The main concern of this model is to estimate and measure the human personality dimension against the job performance (Barrick & Mount, 1991). Over the past few years, many studies had conducted related to personality behaviour with this model. Barrick and Mount (1991) used this model to conduct the research on personality trait in occupation change or turnover job issues. Next, Le et al. (2011) applied this model in conducting the questionnaire in their study on personality trait on job performance. The five main personality trait aspects in this model are openness to experience, consciousness, extraversion, agreeableness and natural reaction.

The main purpose of choosing the popular big five personality traits acts as the job candidate evaluation criteria is because big five personality traits are related to job performance. Caldwell and Burger (1998) had uncovered the evidence that there is linking relationship of big five personality traits to success in job interview. They targeted the applicants from business background who apply job positions such as sales promoter, sales marketing, and sales executives. Their result proved that there is positive correlation between big five personality traits and success in job interview. Thus, identifying the importance of personality traits can filter and rank the unskilled applicants.

i. Openness to Experience

Openness to experience concentrates on the actively looking for learning in order to gain the experience for individual benefit (Wille et al., 2010). It can be explained by using the term of imaginative faculty. It calculates the standard of ingenuity of human (Wille et al., 2010).

ii. Consciousness

Consciousness is the level of group, perseverance, and inspiration in target focusses behaviour (Wille et al., 2010). If human scores higher in this dimension, he or she would make strategy, and will follow it.

iii. Extraversion

Extraversion shows the amount and strengths of capability of work towards the surroundings (Wille et al., 2010). Hence, this can estimate the standard of sociability. Human can be estimated from quiet to outgoing level. If human scores higher on this dimension, it stands for he or she would like to have a new experiences or challenges in work (Wille et al., 2010).

iv. Agreeableness

Agreeableness focuses on the type of public connections which relates to human favours, such as sympathy to tough awareness (Wille et al., 2010). In short, it stands for how much of kindness and friendliness of people to others. People with lower score in this dimension, they are self-interest over interaction with others (Wille et al., 2010). Hence, they always show their selfish and rival nature.

v. Natural Reaction

Natural reaction stands for emotional stability (Wille et al., 2010). It handles human's vulnerability to psychosomatic distress. Therefore, it can estimate the neuroticism and emotional reaction of human. For instance, measure the natural reaction of human by observing the reaction of human if he or she is in stressful situation.

2.6 Recommender Scheme & Filtering Technique

Recommendation system is the program and technology that recommend the relevant items or products to user (Ricci, Shapira, & Rokach, 2015). The recommendation offered are focused on assisting user in various decision-making processes, such as product recommendation, application recommendation, website recommendation, movie recommendation and job recommendation. There are several real applications in recommendation system. For example, product recommendation consists of Amazon (<https://www.amazon.com/>) (Schafer, Joseph, & Riedl, 1999) and eBay (<https://www.ebay.com/>) (Schafer et al., 1999), movie recommendation comprises Netflix (<https://www.netflix.com>) (Koren, Bell, & Volinsky, 2009), and job recommendation includes Monster (<https://www.monster.com/>) (Färber et al., 2003).

Job recommendation system is the recommendation system that able to suggest the relevant job seekers to recruiters or human resource manager (Hong, Zheng, Wang, & Shi, 2013). Generally, job recommendation system can produce a list of job applicants for recruiters job requirements or recommend job to job seeker based on their own preference. There are several of real applications that implement the job recommendation system in their e-recruitment system. JobFinder (<http://www.jobfinder.com/>) used CASPER in the job application subsystem of its e-recruitment system (Bradley & Smyth, 2003). CASPER has two stages of search engine in job recommendation system, they are similarity metrics which allow job seeker to look for job post, and personality trait ranking which can generate the search result based on job seeker's personality trait. Proactive (<http://www.proactiverecruitment.co.uk/>) implements Proactive to improve the job recommendation in its job portal (Lee & Brusilovsky, 2007). Proactive constructs a list of

favourite jobs which is predefined by job seeker, and recommend the job to job seeker based on the collection of favourite job. PROSPECT system employs the information retrieval technique to rank and recommend the job seeker to relevant job offer (Singh et al., 2010). By using information retrieve technique, it allows PROSPECT to extract the important features of job applicant from resume, and rank the job applicants based on the features that has extracted. Absolventen (<http://www.absolventen.at/>) uses eRecruiter to enhance the accurateness of matching between job seeker and job postings (Hutterer, 2011). eReruiteer is the integration of content-based filtering (CBF) technique and knowledge-based recommendation (KBR) technique to filter and rank job applicants.

Based on technical perspective, job recommendation system can be categorized into five main schemes, they are Collaborative Filtering Recommendation (CFR) technique, Content-based Recommendation (CBR) technique, knowledge-based Recommendation (KBR) technique, Reciprocal Recommendation (ReR) technique and Hybrid Recommendation (HyR) technique (Hong et al., 2013).

i. CFR Technique

CFR technique is the one of the most popular candidate filtering scheme in job recruitment system (Al-Otaibi & Ykhlef, 2012). It uses user-to-user correlation method which can find the similarity within a group of users, such as same favourable item, personality traits and preference of work from job seeker (Färber et al., 2003). CFR technique implements a series of known and favour criteria of user to assume the unidentified preference for new candidate. The basic hypothesis of CFR technique is if individuals consist of same rate on items, they are concluded to have the alike behaviour (Su & Khoshgoftaar, 2009). Thus, both individuals

are likely to measure other items similarly. The benefits of using CFR technique is it can work even in the situation where the domain is hard to define or it is unable to analyze automatically (Al-Otaibi & Ykhlef, 2012). This makes the CFR technique become the self-determining of mechanism comprehensible of recommended results. This is because CFR technique algorithm consists of memory based model which works as user-item rating matrix (Adomavicius & Tuzhilin, 2005). The user-item rating matrix is constructed based on predefined behaviour of job seeker. Nevertheless, it cannot support for the large data. For instance, quality of the system reduces when user data become huge (Hu & Pu, 2011).

The most significant approach of using CFR technique is by Färber et al. (2003). They implemented CFR technique in the system which can suggest the book and movie to user. They used Expectation Maximization (EM) algorithm to produce the user-item rating matrix (user-to-book or user-to-movie matrixes) to represent the behaviour of each user. EM algorithm is proposed by Dempster, Laird and Rubin (1977). The basic idea of EM algorithm is find the maximum-likelihood estimation (MLE) from a set of data. MLE is the solution to predict the user-item rating by calculate the mean and variance in a set of data, such as the job seeker's behaviour (Dempster et al., 1977).

ii. CBR Technique

The basic concept of CBR technique is to recommend the item which is cognate to requirements of user (Hong et al., 2013). For example, recommend the job to job seeker based on the job seeker's profile and preference requirements. CBR technique uses the detail information of job seekers' profiles and detail information of job offers to calculate the similarity between both detail information. Therefore, detail information is needed to

implement in CBR technique (Gao, Fu, Chen, & Jiang, 2012). Al-Otaibi & Ykhlef (2012) stated that details information can be acquired by information retrieve (IR) or machine learning in CBR technique.

Yi, Allan, and Croft (2007) implement IR in CBR technique to match the resume of job seeker matching. SRM is a retrieval pattern that able to deduce ideas for a field based on the content which is provided by another field (Lavrenko, Yi, & Allan, 2007). For instance, if two job offers provide “android mobile developer” as the job title field, the job applicant who has “java programming language” or “kotlin programming language” is likely to be selected based on IR in CBR technique.

Besides that, Paparrizos, Cambazoglu, and Gionis (2011) employ supervised machine learning model in CBR technique to construct the job recommendation system in their e-recruitment system. They trained a machine learning model that can forecast the next suitable job for job applicants based on their previous working experience and details information from job offers. With machine learning, it is able to do the automation suggestion function. However, supervised machine learning requires a huge user profile data in order to do the machine learning (Paparrizos et al., 2011). They used five million available job applicant’s profiles from internet as their dataset. They extracted the main features from the job applicant’s profile, such as full name, past working experience, education background and geolocation. They used the Decision Table Naïve Bayes (DTNB) (Hall & Frank, 2008) as their machine learning algorithm. DTNB is a basic Bayesian network in which the decision table works as the conditional probability table (Hall & Frank, 2008).

iii. KBR Technique

The principle of KBR is to recommend the job to job hunter based on the inference engine which consist of job hunter's needs and preference (Burke, 2002). Inference engine works as the knowledge based system that includes all the information needs for suggestion the job to job seeker, such as the rules, pattern, and requirements for jobs. Burke (2002) stated that rule and patterns are two main components to suggest the job to job seeker based on functional knowledge of how jobs to meet job seeker's requirements or how job seekers meets recruiter's needs. In the other word, the knowledge in inference engine is constructed based on the rule and pattern (Hong et al., 2013). For instance, the rule can be set that if job seeker who has more than one year working experience on specific job sector, he or she is likely to have better job performance. And if job seeker has better job performance, then he or she will be recommended for recruiter.

However, Burke (2002) also stated that the main difficulties of KBR is the knowledge acquisition and knowledge engineering. Knowledge acquisition plays important role in knowledge based technique. Incorrect knowledge built in the database brings the many false hits results. Moreover, gathering the knowledge to form the database in difficult because it is hard to convert the knowledge from experts into the machine-readable knowledge. Lee and Brusilovsky (2007) implements KBR technique in their job recommendation system. They applied the Proactive which acts as the ontology checker to do the matching between job seeker and job offers (Lee & Brusilovsky, 2007). Ontology is a comparatively overall knowledge-based system which consists of all the information about the attribute of job application and relationships between job seeker and job. By using the ontology checker, it

can recommend the job to job seeker based on the collection of predefined favourite job from job seekers.

iv. ReR Technique

ReR technique is bilateral kind of job recommendation system (Hong et al., 2013). Bilateral kind of job recommendation system refers to two sides of preference between both parties (Pizzato et al., 2010). In the other words, ReR technique takes all preferences from job seeker and recruiters, and return the satisfied result for both parties. For instance, job seeker can get the job which is fit to his or her preferences, meanwhile, the job seeker is match to their job requirement as well. Yu, Liu, and Zhang (2011) implement ReR technique in their proposed recruitment system. They use the similarity calculation method (Yu et al., 2011) to calculate reciprocal value. The reciprocal value acts as the ratings for each job seekers based on the preference of user to jobs, and preference of job requirements.

v. HyR Technique

HyR technique becomes popular after Färber et al. (2003) proposed the first hybrid recommendation system which can solve the candidate filtering and job recommendation problem. HyR technique integrate two or more job recommendation scheme in order to get the better results with less of defect from any party (Burke, 2002). Generally, HyR technique combines two or more recommendation techniques to get the result that is satisfied for both job seeker and recruiter. One of the examples of recommendation system that implement the HyR is developed by Malinowski et al. (2006). Their proposed system is the extended version of the model by Färber et al. (2003). They integrated both CFR and CBR techniques simultaneously in their bilateral person to job recommendation system.

At first, Malinowski et al. (2006) developed the CV-recommender which mainly focus on the recruiter's side. The CV-recommender gathers resume of job applicants and job profiles, such as job title, job description and job requirements. On the other hand, they developed the Job-recommender that mainly focus on job seeker's side. Job-recommender collects job profiles and preference of job seekers. They implemented the EM algorithm (Dempster et al., 1977) to calculate the probability of job applicant to job offer. The best candidate will be selected based on the highest probability of job applicant to job offer.

Apart from that, Fuzzy Multiple Criteria Decision-Making (FMCDM) model is another example of HyR technique in job recommendation system (Al-Otaibi & Ykhlef, 2012). FMCDM model integrates fuzzy set theory with Multiple Criteria Decision-Making (MCDM) for getting better result in job recommendation system (Chen, 2009). Generally, MCDM usually uses to handle the decision-making problem that relates to multiple conflicting objective (Belton & Stewart, 2002). By using fuzzy membership function in MCDM, MCDM can use fuzzy linguistic variable to evaluate and express decision-making group's judgement towards the selection criteria in e-recruitment system.

One of the example of FMCDM in job recommendation system is from Chen (2009) who had developed a system that can determine the best suit of personality traits and skill of candidates in job matching and candidate filtering by using the fuzzy analytic hierarchy process (F-AHP). He took the questionnaire assessment first before weight for each attribute was calculated based on F-AHP. The more details of FMCDM will be discussed in the next section.

2.6.1 Fuzzy Multiple Criteria Decision-making (FMCDM) Model

FMCDM is the integration of fuzzy set theory in the Multi-criteria Decision-making (MCDM) with the fragmentary and fuzzy information (Varmazyar & Nouri, 2014). It works as a coordinator for deduction in decision-making mechanism under the MCDM that absence of integrated and definite information (Gutiérrez & Carmona, 1995). It is advanced from the classical MCDM approach which adds the fuzzy set theory into MCDM. Adding fuzzy set theory makes FMCDM is more towards to human behaviours as it can handle uncertainty problems which are difficult to solve by normal MCDM. Based on the Chambers Dictionary (Chambers, 1998), the definition of uncertainty is indefinitely or vagueness; uncleanness or dubiousness. Practically, Zimmermann (2000) stated the definition of uncertainty in MCDM is a circumstance that human cannot induce about the information or knowledge which is either in quantitatively or qualitatively, and it is hard to adequately depict, define or anticipate definitely and numerically a term, habits, or feature.

The fundamental principle of FMCDM is applying the fuzzy membership function, such as triangular fuzzy membership function to work as linguistic variable that able to express the decision-making (DM) group's judgements towards criteria with MCDM approach. MCDM is a set of techniques that focus on handling the problem which includes multiple complicate objectives (Belton & Stewart, 2002). It is a collection of mathematical algorithm which is designed for solving the decision-making problem based on multiple criteria. The basic working principle of a MCDM approach is to have decision weight for each criterion and decision matrix for alternative as input, and recommended best alternative as output based on the MCDM approach.

i. Decision-making (DM) group

In MCDM, DM plays vital role in entire decision-making process. This is because DM is in-charge of structuring the overall decision problem, such as evaluation of alternatives, definition of criteria, and judgement of final decision made. DM is a team of experts who has the relevant knowledge relating to both alternative and criteria based on the main domain (Tzeng & Huang, 2011). For example, recruiter and human resource manager is the expert for job recruitment problem

ii. Criteria

Criteria is a term which uses to indicate the characteristic, feature or aspect which can affect the decision-making process in MCDM (Belton & Stewart, 2002). All criteria are predefined by the DM group. For example, the criteria for job recruitment problem are job seeker's profile like education background, characteristic, personality traits, working experience, preference of working style, and job offer's profile such as requirement of job and salary offer.

iii. Weight

In MCDM, weight is the term which uses to represent the importance of criteria during the decision-making process (Tzeng & Huang, 2011). DM group is responsible in assigning the importance weight to each criterion based verbal judgement scale. For example, verbal judgement can be ranged from not equal to extreme more (not equal, equal, moderate, more and extreme more). On the other hands, this verbal judgement is corresponding to numerical judgement which can be represented between absolute value (1, 3, 5, 7, 9), and the numerical

judgement will be used in MCDM algorithm. Equation (1) illustrates the weight for n criterion.

$$W = [w_1, w_2, w_3, \dots, w_n], j = 1, 2, 3, \dots, n \quad (1)$$

where n is the total number of criteria.

iv. Alternative

Alternative implies the option or choice that available to be selected and recommended by MCDM (Belton & Stewart, 2002). For example, job seeker is the alternative in job recruitment problem.

v. Decision Matrix for all alternative

In MCDM, matrix format is implemented in structuring the decision-making problem for easy analysis in decision-making process (Tomaszewski, 2015). It includes score of all alternative and weight of each criterion. A $m \times n$ decision matrix is constructed based on $A = A_1 + A_2 + \dots + A_m$ which represents a set of alternative, $C = C_1 + C_2 + \dots + C_n$ which is a set of criteria, and $D = D_1 + D_2 + \dots + D_{dm}$ which is a set of DM. Equation (2) demonstrates the decision matrix K for all alternative based on each criterion.

$$K = \begin{matrix} & C & & C_1 & \dots & C_n \\ \begin{matrix} A_1 \\ \vdots \\ A_m \end{matrix} & \begin{bmatrix} X_{11} & \dots & X_{1n} \\ \vdots & \ddots & \vdots \\ X_{m1} & \dots & X_{mn} \end{bmatrix} \end{matrix}, i = 1, 2, \dots, m; j = 1, 2, \dots, n \quad (2)$$

where m is the total number of alternatives; n is the total number of criteria

Based on study by Hwang and Yoon (2012) and Zimmermann (2000), the techniques of MCDM can be classified into two main categories. The first category is Multiple Objective

Decision-making (MODM). MODM is applied when the decision space is successive (Hwang & Yoon, 2012). Hence, MODM deals with the problem when alternatives are not predefined (Zimmermann, 2000). From other perspective, MODM is implemented if objective of decision-making problem is to devise the most prospective alternative with respect to limited design space or resource. One of example of MODM problem is to select a concept for aircraft design (Mosher, 1999). The researcher employs Genetic Algorithm (GA) to design the best concept for aircraft design, but in the limited resource of combination of spacecraft component (Mosher, 1999). GA algorithm becomes the most popular technique in MODM because it can comparatively quickly to get the global optimums by using “black-box” fitness approach in GA (Chen, Han, Liu, Jiang, & Zhao, 2012).

The second category of MCDM is Multiple Attribute Decision-making (MADM). MADM is collaborated with decision problem with a discrete decision space (Hwang & Yoon, 2012). It mainly deals with the problem that consists of a set of predefined alternatives. The example of MADM is recommend the best candidate based on a set of job seeker (Kelemenis, Ergazakis, & Askounis, 2011). The most significant difference between both MCDM categories is the absence of predefined set of alternative (Xu & Yang, 2001). This is because the MODM is suitable for designing the alternative or searching the prospective alternative based on infinite number of alternative (continuous space) but MADM is suitable for recommend the alternatives based on set of predetermined alternative (discrete space), such as the e-recruitment problem that involves a set of predefined job seeker.

The fundamental of MADM consists of limited series of alternatives which the system needs to choose, judge and rank all the alternatives based on weight of a series of limited attributes

or criteria. There are several techniques that can implement in MADM. They are Elimination Et Choix Tradiosant la REaite (ELECTRE), Technique for Ordering Preference by Similarity to Ideal Solution (TOPSIS), Analytic Network Process (ANP) and Visekriterikumsko Kompromisno Rangiranje (VIKOR) (Mardani, Jusoh, & Zavadskas, 2015). One of the significant MADM example is by Saaty (1990) who developed the employee evaluation system by using AHP algorithm (Saaty, 1996). AHP calculation steps (Saaty, 1996) are demonstrated as following:

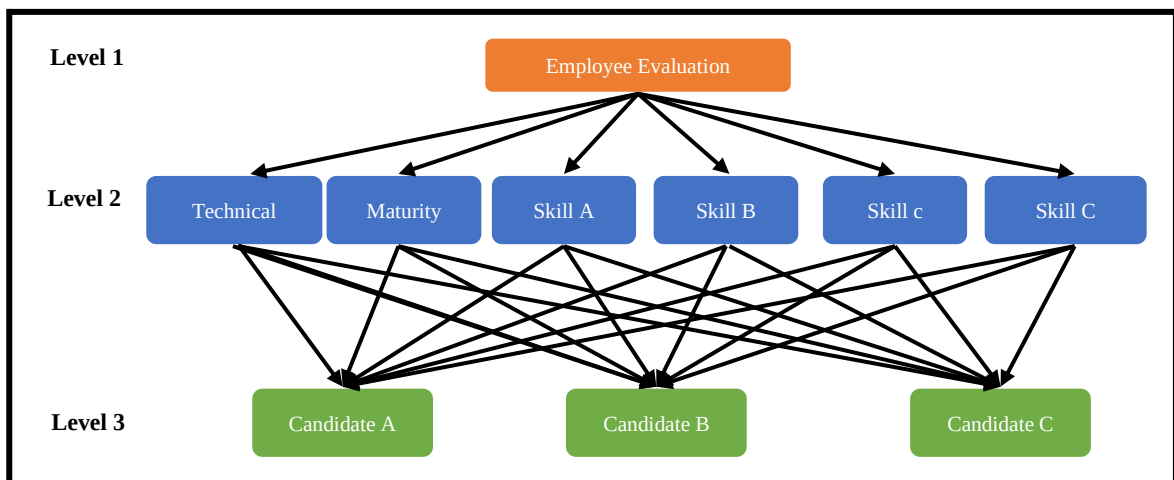


Figure 2.5: Hierarchical structure of employee evaluation system (Saaty, 1996).

Step 1: Problem modeling. In this step, objective and evaluation factors for the decision-making process is determined by DM group. A hierarchical structure is constructed Based on the objective and evaluation factors. The top level indicates the main objective for decision-making problem, second level implies the evaluation factors or criteria, and the last level is the alternative. Figure 2.5 illustrates the hierarchy structure of employee evaluation system (Saaty, 1996).

Step 2: Construct pair-wise comparison matrix for criteria. In this step, a pair-wise

comparison matrix is constructed based on the relative weight of each criterion with respect to the main objective of the decision-making problem. The relative weight of each criterion is determined by DM groups without the numerical judgement but the relative verbal judgement with the fundamental scale of AHP (Saaty, 1996) as demonstrated in Table 2.4. There are N number of criteria, the pair-wise comparison of criterion i with criterion j generate a square matrix $A_{1N \times N}$, where a_{ij} implies the relative weight of criterion i with respect to criterion j . Pair-wise comparison matrix is constructed in a positive reciprocal matrix format as illustrated in Equation (3).

Table 2.4: Intensity of importance scale (Saaty, 1996).

Relative importance (a_{ij})	Description
1	Equal importance of i and j
2	Weak
3	Moderate importance of i over j
4	Moderate Plus
5	Strong importance of i over j
6	Strong Plus
7	Very strong importance of i over j
8	Very, very strong
9	Absolute importance of i over j

$$A = \begin{bmatrix} 1 & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & 1 \end{bmatrix} \quad (3)$$

$$\text{where } a_{ij} = 1/a_{ji}.$$

Step 3: Calculate relative normalized weight for each criterion (W_i). In this step, the Logarithmic Least Square Method (geometric mean, GM_i) of i th row of each criterion is calculated in Equation (4) (Ishizaka & Labib, 2011). The relative normalized weight W_i of each criterion i is calculated in Equation (5), which is divided GM_i by summation of GM_i

(Ishizaka & Labib, 2011). Equation (6) implies the matrix A_2 which lists all the relative normalized weight W_i .

$$GM_i = \left(\prod_{j=1}^N a_{ij} \right)^{1/N} \quad (4)$$

$$W_i = \frac{GM_i}{\sum_{j=1}^N GM_i} \quad (5)$$

$$A_2 = [W_i, \dots, W_N]^T, i = 1, 2, 3, \dots, N \quad (6)$$

where N is the total number of criteria.

Step 4: Calculate the Consistency Ratio (CR). In this step, matrix A_3 and A_4 are constructed based on Equation (7) and (8) respectively. The maximum of eigen value (λ_{max}) which is the average of matrix A_4 (Ishizaka & Labib, 2011). Once the eigen value is obtained, consistency index (CI) is calculated in Equation (9) (Ishizaka & Labib, 2011). The CR is then calculated in Equation (10) (Ishizaka & Labib, 2011) based on the random index (RI) (Saaty, 1996) as demonstrated in Table 2.5. Saaty (1990) had stated that pair-wise matrix can only be accepted if CR is lower than 0.1.

$$A_3 = A_1 \times A_2 \quad (7)$$

$$A_4 = \frac{A_3}{A_2} \quad (8)$$

$$CI = \frac{\lambda_{max} - N}{N - 1} \quad (9)$$

where N is dimension of matrix; λ_{max} is maximum number of eigen value

$$CR = \frac{CI}{RI} \quad (10)$$

where RI is random index (Saaty, 1996).

Table 2.5: Random index (Saaty, 1996).

Number of factors	RI
1	0.00
2	0.00
3	0.58
4	0.90
5	1.12
6	1.24
7	1.32
8	1.41
9	1.45

Step 5: Construct pair-wise comparison matrix for alternative. . In this step, D number of $A \times A$ pair-wise comparison matrixes are constructed, where D is the total number of criteria, and A is the total number of alternatives, based on preference of each alternative with respect to the particular criterion. The preference of each alternative is determined by DM groups without the numerical judgement but the relative verbal judgement with the basic scope of AHP (Saaty, 1996) which is demonstrated in Table 2.4. Equation (11) demonstrates the pair-wise comparison matrix for A of alternative for criterion k .

$$P_k = \begin{bmatrix} 1 & \cdots & P_{1A} \\ \vdots & \ddots & \vdots \\ P_{A1} & \cdots & 1 \end{bmatrix} \quad (11)$$

where $P_{ij} = 1/P_{ji}$; D is the total number of criteria; A is total number of alternatives.

Step 6: Aggregation. In this step, global priority (S_i) of candidate i is calculated by synthesizing local priorities across all the criteria in Equation (12) (Ishizaka & Labib, 2011). Before that, each comparison matrix of alternative needs to be normalized by summation of each column of the matrix (P_{ij}^1), then averaging the normalized row of the matrix (V_i), as

shown in Equation (13) and (14) (Ishizaka & Labib, 2011). The highest global priority indicates the best alternatives to be selected in decision-making problem (Saaty, 1996).

$$S_i = \sum_{k=1}^N (V_{ik} W_k), i = 1, 2, 3, \dots, M; k = 1, 2, 3, \dots, N \quad (12)$$

where V_{ik} is priority vector of alternative i with respect to criterion k ; W_k is criteria weight as shown in matrix A_2 in Equation (6); M is total number of alternatives; N is total number of criteria.

$$P_{ij}^1 = \frac{p_{ij}}{\sum_{i=1}^M p_{ij}}, i, j = 1, 2, 3, \dots, M \quad (13)$$

where M is total number of alternatives.

$$V_i = \frac{1}{M} \sum_{j=1}^M P_{ij}^1, i = 1, 2, 3, \dots, M \quad (14)$$

where M is total number of alternatives.

MCDM is good to solve the multiple criteria decision-making problem. However, it becomes unrealistic when applying crisp values for a subjective decision-making, especially when the data information obtained is indistinct, ambiguous and fuzzy. This is because MCDM is unable to examine well with abstract, uncertainty and indefinite attributes or characteristics in human's judgement (Chen, 2009). For example, it is unable to judge the job seeker's responsible in the normal crisp or absolute value of three to represent the moderate weak for responsible of a job seeker. Therefore, applying the fuzzy set theory in the MCDM can solve the uncertainly and indistinctly problem in the real world (Chang & Wang, 2009). Chen (2009) modified Saaty's original AHP algorithm by changing the pair-wise comparison value into fuzzy membership function such as triangular fuzzy number. The researcher used

the triangular fuzzy number to express the relative important for each criteria, and applied the normalized pair-wise fuzzy decision matrix (Buckley, 1985), which is normalizing the pair-wise fuzzy decision matrix by using geometric mean in Equation (16).

The most recent FMCDM techniques are fuzzy AHP (F-AHP), fuzzy TOPSIS (F-TOPSIS), fuzzy Analytic Network Process (F-ANP), fuzzy VIKOR (F-VIKOR), Fuzzy ELECTRE (F-ELECTRE), and hamming distance method (Mardani et al., 2015).

2.6.1.1 Fuzzy Analytic Hierarchy Process (F-AHP)

AHP is designed by Saaty in 1970 (Saaty, 1996). The AHP is the algorithm that uses pair-wise comparison to access the relative important of alternatives and criteria (Varmazyar & Nouri, 2014). From other perspective, it takes pair-wise comparison of each alternative with respect to each criteria, and provides a decision-making engine or apparatus for decision-making problem based on the pair-wise comparison. F-AHP is one of the FMCDM that integrates the fuzzy set theory to general MCDM by changing the pair-wise comparison value into fuzzy membership function. There are many researchers had implemented F-AHP in the FMCDM problem (Chen, 2009; Chang & Wang, 2009; Varmazyar & Nouri, 2014). For example, Chen (2009) who had developed a system that can determine the best suit of personality traits and skill of candidates in job matching and candidate filtering by using the information statistics and AHP. He took the questionnaire assessment first before weight for each attribute. He applied the normalized method by Buckley (1985) which is normalized the pair-wise fuzzy decision matrix by using geometric mean in Equation (16), and created the local priority vector, which is similar to crisp AHP method. Then, the final score of

assessment for the application is calculated based on the global priority weight of each alternative (Chen, 2009).

Apart from normalized method by Buckley (1985), another common approach to normalize pair-wise fuzzy decision matrix is extent analysis method (Chang, 1996). Extent analysis method uses additive normalization method to normalize the pair-wise fuzzy decision matrix, then determine the priority vector through degree of possibility. More detail of extent analysis method is discussed in section 2.6.1.3-Fuzzy Analytic Process (F-ANP).

By using the F-AHP, every decision can be easily made by specifying preferable attributes in the form of natural language or numeric value (Varmazyar & Nouri, 2014). Generally, the main stages of AHP consists of problem definition, construction of hierarchy, questionnaire design and data collection, and testing methodology (Chen, 2009). Figure 2.5 shows the hierarchy of the recruitment problem (Varmazyar & Nouri, 2014). It is clearly shown the F-AHP can syndicate the preferable attributes with existing data, and it plays a main role in calculating the series of weight vectors which is needed for selection from main aspects. The step of F-AHP (Chen, 2009) is demonstrated as following:

Step 1: Problem modeling. In this step, objective and evaluation factors for the decision-making process is determined by DM group. A hierarchical structure is constructed based on the objective and evaluation factors. The top level indicates the main objective for decision-making problem, second level implies the evaluation factors or criteria, and the last level is the alternative. Figure 2.5 illustrates the example of hierarchy structure of employee evaluation system (Saaty, 1996).

Step 2: Construct pair-wise fuzzy comparison matrix for criteria. In this step, a pair-wise fuzzy comparison matrix is constructed based on the relative weight of each criterion with respect to the main objective of the decision-making problem. The relative weight of each criterion is determined by DM groups without the numerical judgement but the linguistic terms are applied to the pair-wise comparison as demonstrated in Table 2.6. There are N number of criteria, the pair-wise comparison of criterion i with criterion j generate a square matrix $A_{1N \times N}$, where a_{ij} implies the relative weight of criterion i with respect to criterion j . Pair-wise comparison matrix is constructed in a positive reciprocal matrix format as illustrated in Equation (15).

Table 2.6: Fuzzy linguistic terms with fuzzy number for each criteria.

Linguistic Terms	Fuzzy Number
Very Poor (VP)	(0,0,0.2)
Poor (P)	(0.05,0.2,0.35)
Medium Poor (MP)	(0.2,0.35,0.5)
Fair (F)	(0.35,0.5,0.65)
Medium Good (MG)	(0.5,0.65,0.8)
Good (G)	(0.65,0.8,0.95)
Very Good (VG)	(0.8,1.0,1.0)

$$\tilde{A}_k = \begin{bmatrix} 1 & \cdots & \tilde{a}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{a}_{n1} & \cdots & 1 \end{bmatrix} \quad (15)$$

where $\tilde{a}_{ij} = (a_{ij}, b_{ij}, c_{ij})$.

Step 3: Calculate relative fuzzy normalized weight for each criterion ($\tilde{W}_i$). In this step, the Logarithmic Least Square Method (geometric mean, $\tilde{GM}_i$) of i th row of each criterion is calculated in Equation (16) (Varmazyar & Nouri, 2014). The relative fuzzy normalized weight W_i of each criterion i is calculated in Equation (17), which is divided $\tilde{GM}_i$ by

summation of $\widetilde{GM}_i$ (Varmazyar & Nouri, 2014). Equation (6) implies the matrix A_2 which lists all the relative normalized weight $\widetilde{W}_i$.

$$\widetilde{GM}_i = (\prod_{j=1}^N \widetilde{a}_{ij})^{1/N} \quad (16)$$

where $\widetilde{GM}_i = (\widetilde{GM}_{ir1}, \widetilde{GM}_{ir2}, \widetilde{GM}_{ir3})$; $\widetilde{GM}_{ir1} = (\prod_{j=1}^N \widetilde{a}_{ir1,j})^{1/N}$; $\widetilde{GM}_{ir2} = (\prod_{j=1}^N \widetilde{a}_{ir2,j})^{1/N}$; $\widetilde{GM}_{ir3} = (\prod_{j=1}^N \widetilde{a}_{ir3,j})^{1/N}$; N indicates the total number of criteria.

$$\widetilde{W}_i = \frac{\widetilde{GM}_i}{\sum_{j=1}^N \widetilde{GM}_i} \quad (17)$$

where $\widetilde{W}_i = (\widetilde{W}_{ir1}, \widetilde{W}_{ir2}, \widetilde{W}_{ir3})$; $\widetilde{W}_{ir1} = \frac{\widetilde{GM}_{ir1}}{\sum_{j=1}^N \widetilde{GM}_{ir1j}}$; $\widetilde{W}_{ir2} = \frac{\widetilde{GM}_{ir2}}{\sum_{j=1}^N \widetilde{GM}_{ir2j}}$; $\widetilde{W}_{ir3} = \frac{\widetilde{GM}_{ir3}}{\sum_{j=1}^N \widetilde{GM}_{ir3j}}$; N indicates the total number of criteria.

Step 4: Calculate the Consistency Ratio (CR). In this step, matrix A_3 and A_4 are constructed based on Equation (7) and (8) respectively. The maximum of eigen value (W_i) which is the average of matrix A_4 (Ishizaka & Labib, 2011). If A_i is consistent, then $\widetilde{A}_i$ is also consistent (Soloukdar & Parpanchi, 2015). Once the eigen value is obtained, consistency index (CI) is calculated in Equation (9) (Ishizaka & Labib, 2011). The CR is then calculated in Equation (10) (Ishizaka & Labib, 2011) based on the random index (RI) (Saaty, 1996) as demonstrated in Table 2.5. Saaty (1990) had stated that pair-wise matrix can only be accepted if CR is lower than 0.1.

Step 5: Construct pair-wise fuzzy comparison matrix for alternative. . In this step, N number of $M \times M$ pair-wise fuzzy comparison matrixes are constructed, where N is the total number of criteria, and M is the total number of alternative, based on preference of each alternative with respect to a particular criterion. The preference of each alternative is determined by DM groups without the numerical judgement but the linguistic terms are

applied to the pair-wise comparison as demonstrated in Table 2.7. Equation (18) demonstrates the pair-wise fuzzy comparison matrix for M of alternative for criterion k .

Table 2.7: Fuzzy linguistic terms with fuzzy number for each alternative.

Linguistic Terms	Fuzzy Number
Very Low (VL)	(0,0,0.2)
Low (L)	(0.05,0.2,0.35)
Medium Low (ML)	(0.2,0.35,0.5)
Medium (M)	(0.35,0.5,0.65)
Medium High (MH)	(0.5,0.65,0.8)
High (H)	(0.65,0.8,0.95)
Very High (VH)	(0.8,1.0,1.0)

$$\tilde{P}_k = \begin{bmatrix} 1 & \cdots & \tilde{p}_{1M} \\ \vdots & \ddots & \vdots \\ \tilde{p}_{M1} & \cdots & 1 \end{bmatrix} \quad (18)$$

where $\tilde{p}_{ij} = (a_{ij}, b_{ij}, c_{ij})$.

Step 6: Aggregation. In this step, global priority ($\tilde{S}_i$) of candidate i is calculated by synthesizing local priorities across all the criteria in Equation (19) (Varmazyar & Nouri, 2014). Before that, each comparison matrix of alternative needs to be normalized by summation of each column of the matrix ($\tilde{P}_{ij}^1$), then averaging the normalized row of the matrix ($\tilde{V}_i$), as shown in Equation (20) and (21) (Varmazyar & Nouri, 2014). The highest global priority indicates the best alternatives to be selected in decision-making problem (Saaty, 1996).

$$\tilde{S}_i = \sum_{k=1}^N (\tilde{V}_{ik} \tilde{W}_k), i = 1, 2, 3, \dots, M; k = 1, 2, 3, \dots, N \quad (19)$$

where $\tilde{V}_{ik}$ is priority vector of alternative i with respect to criterion k ; $\tilde{W}_k$ is criteria weight; M is total number of alternatives; N is total number of criteria.

$$\tilde{P}_{ij}^1 = \frac{p_{ij}}{\sum_{i=1}^M p_{ij}}, i, j = 1, 2, 3, \dots, M \quad (20)$$

where M is total number of alternatives.

$$\tilde{V}_i = \frac{1}{M} \sum_{j=1}^M \tilde{P}_{ij}^1, i = 1, 2, 3, \dots, M \quad (21)$$

where M is total number of alternatives.

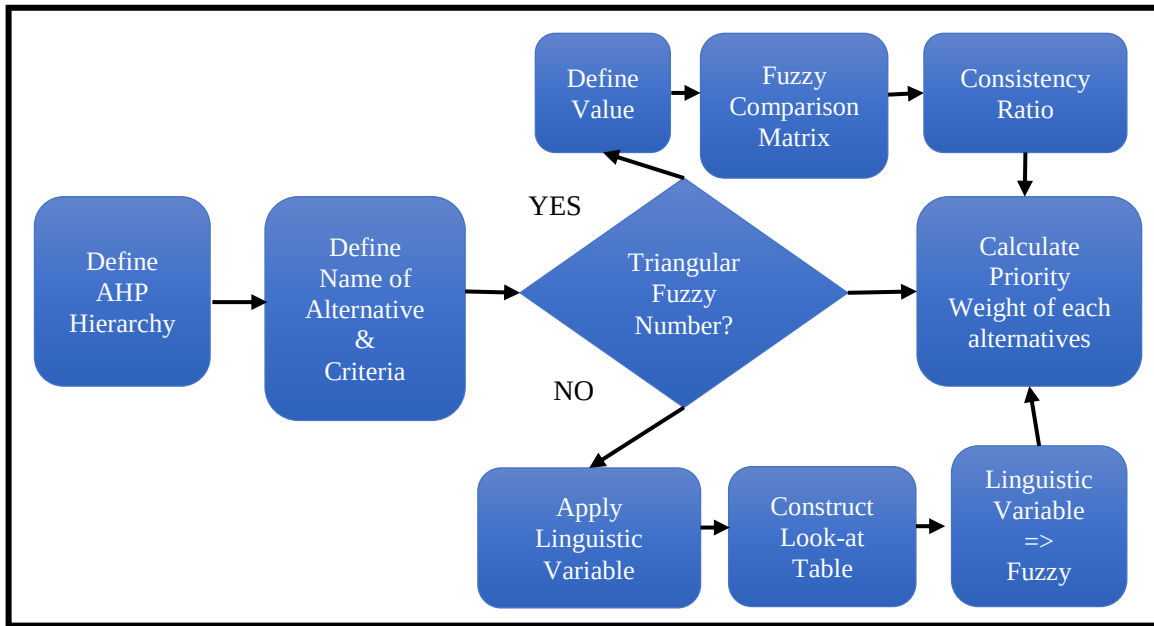


Figure 2.6: Step of F-AHP (Varmazyar & Nouri, 2014).

2.6.1.2 Fuzzy TOPSIS (F-TOPSIS)

Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) technique was first proposed by Hwang and Yoon in 1987 (as cited in Hwang & Yoon, 2012). The main idea of this technique is choosing the best alternative which has the shortest distance from Positive Ideal Solution (PIS), and the farthest distance from the Negative Ideal Solution

(NIS) (Kelemenis et al., 2011). PIS is the solution which can maximize the benefit of attributes, and minimize the cost needed, whereas the NIS is the solution that minimize the benefit of attribute, and maximize the cost needed (Kelemenis et al., 2011). It uses the linguistics variables to represent the fuzzy number to evaluate the weight vectors of attribute and rating of alternatives. One of the examples of F-TOPSIS is from (Mammadova & Jabrayilova, 2014). They implemented this technique to solve the personnel selection problem. Figure 2.7 shows the general steps in F-TOPSIS which is adapted from Ertuğrul and Karakaşoğlu (2008).

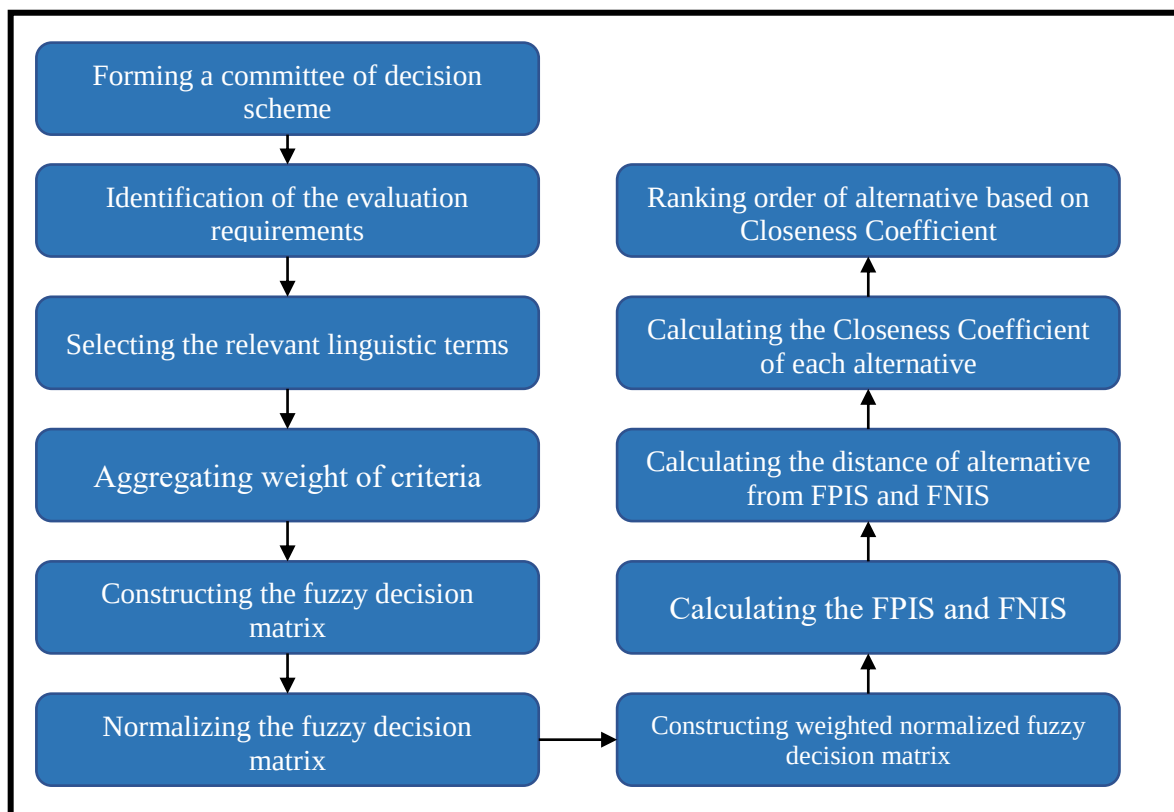


Figure 2.7: General steps in F-TOPSIS (Ertuğrul & Karakaşoğlu, 2008).

Based on the TOPSIS technique that proposed by Chen (2000), Ertuğrul and Karakaşoğlu (2008) and Sun and Lin (2009), the steps of F-TOPSIS are demonstrated as following:

Step 1: Forming DM group. A group of K numbers of experts is formed based on decision-making domain. For example, human resource manager and recruiters are the experts for job recruitment problem.

Step 2: Constructing fuzzy decision matrix for alternatives. A group of K numbers of experts is formed based on decision-making domain. For example, human resource manager and recruiters are the experts for job recruitment problem. DM group is responsible on assigning ratings alternatives with respect to each criterion by using the fuzzy linguistic terms, as illustrated in Table 2.7. The linguistic terms are then converted into fuzzy membership function, such as triangular fuzzy membership function (a_i, b_i, c_i) or trapezium fuzzy membership function (a_i, b_i, c_i, d_i) . A M alternatives and N criteria ($M \times N$) fuzzy decision matrix for alternative can be implied as (Chen, 2000) in Equation (22).

$$\tilde{D}_{(k)} = \begin{matrix} & C & & C_1 & \dots & C_N \\ \begin{matrix} A_1 \\ \vdots \\ A_M \end{matrix} & \begin{bmatrix} \tilde{x}_{11} & \dots & \tilde{x}_{1N} \\ \vdots & \ddots & \vdots \\ \tilde{x}_{M1} & \dots & \tilde{x}_{MN} \end{bmatrix} \end{matrix}, i = 1, 2, \dots, M; j = 1, 2, \dots, N \quad (22)$$

where $\tilde{x}_{ij} = (l_{ij}, m_{ij}, u_{ij})$ is indicated as the rating of alternative i with respect to criterion j , which is assigned by expert k ; M is the total number of alternatives; N is total number of criteria.

Step 3: Assigning importance weights for each criterion. DM group is responsible on assigning importance weights to each criterion by using the fuzzy linguistic terms, as illustrated in Table 2.6. The linguistic terms are then converted into fuzzy membership function, such as triangular fuzzy membership function (a_i, b_i, c_i) or trapezium fuzzy membership function (a_i, b_i, c_i, d_i) .

Step 4: Constructing a fuzzy aggregated decision matrix. The fuzzy decision matrix from Equation (22) needs to be aggregated in order to construct the fuzzy aggregated decision matrix. By using fuzzy WAM method (Forman & Peniwati, 1998), fuzzy aggregated decision matrix can be constructed with respect to each criterion from all experts in DM groups, as illustrated in Equation (23).

$$\tilde{x}_{ij} = \sum_{k=1}^P \left(l_k \tilde{x}_{ij}^{(k)} \right), i = 1, 2, \dots, M, j = 1, 2, \dots, N \quad (23)$$

where l_k is the importance weight of expert k , $l_k > 0$; $\sum_{k=1}^P (l_k) = 1$; p indicates the total number of connoisseurs in DM group; $\tilde{x}_{ij}$ is the fuzzy rating of alternative i with respect to criterion j ; $\tilde{x}_{ij}^{(k)}$ refers to fuzzy rating of alternative i with respect to criterion j which is assigned by expert k ; M is the total number of alternatives; N is total number of criteria.

Step 5: Constructing fuzzy normalized aggregated decision matrix. The fuzzy aggregated decision matrix needs to be normalized. The fuzzy normalized aggregated decision matrix is formed in $\tilde{R}$ format (Sun & Lin, 2009), as shown in Equation (24), and performs normalization by fuzzy normalization method which is proposed by Chen (2000), as illustrated in Equation (25).

$$\tilde{R} = \begin{pmatrix} \tilde{r}_{11} & \cdots & \tilde{r}_{1N} \\ \vdots & \ddots & \vdots \\ \tilde{r}_{M1} & \cdots & \tilde{r}_{MN} \end{pmatrix}, i = 1, 2, 3, \dots, M, j = 1, 2, 3, \dots, N \quad (24)$$

$$\tilde{R} = [\tilde{r}_{ij}]_{m \times n} \quad i = 1, 2, 3, \dots, m; j = 1, 2, 3, \dots, n \quad (25)$$

$$\text{where } \tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*} \right), c_j^* = \max_i c_{ij} \quad j \in A \text{ and } \tilde{r}_{ij} = \left(\frac{a_{ij}^-}{c_{ij}^-}, \frac{a_{ij}^-}{c_{ij}^-}, \frac{a_{ij}^-}{c_{ij}^-} \right), c_j^- =$$

$\min_i c_{ij} \ j \in B$. A stands for benefit criteria, and B stands for negative criteria like cost salary.

Step 6: Constructing fuzzy weighted normalized aggregated decision matrix. The fuzzy weighted normalized aggregated decision matrix ($\tilde{V}$), as shown in Equation (26) can be constructed by multiplication of each rating of alternative to each criteria, as illustrated in Equation (27) (Chen, 2000).

$$\tilde{V} = \begin{pmatrix} \tilde{v}_{11} & \cdots & \tilde{v}_{1N} \\ \vdots & \ddots & \vdots \\ \tilde{v}_{M1} & \cdots & \tilde{v}_{MN} \end{pmatrix}, i = 1, 2, 3, \dots, M, j = 1, 2, 3, \dots, N \quad (26)$$

$$\tilde{V} = [\tilde{v}_{ij}]_{m \times n} \ i = 1, 2, 3, \dots, m; j = 1, 2, 3, \dots, n \quad (27)$$

where $\tilde{v}_{ij} = \tilde{r}_{ij}(\cdot) \tilde{w}_j$, $\tilde{w}_j$ defined as the importance weighted of criterion C_j .

Based on Ertuğrul and Karakaşoğlu (2008), normalized positive triangular fuzzy number can be concluded as the elements $\tilde{v}_{ij}$, $\forall i, j$; M is total number of alternatives; N is total number of criteria.

Step 7: Defining Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS). FPIS (A^+) and FNIS (A^-) can be defined by using Equation (28) and (29) (Chen, 2000).

$$A^* = (\tilde{v}_1^*, \tilde{v}_2^*, \tilde{v}_3^*, \dots, \tilde{v}_n^*) \quad (28)$$

$$A^- = (\tilde{v}_1^-, \tilde{v}_2^-, \tilde{v}_3^-, \dots, \tilde{v}_n^-) \quad (29)$$

where $\tilde{v}_1^* = \max_i \{\tilde{v}_{ij}\}$ and $\tilde{v}_1^- = \min_i \{\tilde{v}_{ij}\}$ $i = 1, 2, 3, \dots, m; j =$

$1, 2, 3, \dots, n$.

Step 8: Calculating distance of each alternative from FPIS and FNIS. The distance of alternative i from FPIS (d_i^+) as Equation (30), and the distance of alternative i from FNIS (d_i^-) as Equation (31). The distance for both FPIS and FNIS can be calculated using Equation (32) (Wang & Lee, 2009).

$$d_i^+ = \sum_{j=1}^N d(\tilde{v}_j, \tilde{v}_j^+), i = 1, 2, \dots, M, j = 1, 2, \dots, N \quad (30)$$

$$d_i^- = \sum_{j=1}^N d(\tilde{v}_j, \tilde{v}_j^-), i = 1, 2, \dots, M, j = 1, 2, \dots, N \quad (31)$$

$$d(A_1, A_2) = \sqrt{\frac{1}{3} [(a_1 - a_2)^2 + (b_1 - b_2)^2 + (c_1 - c_2)^2]} \quad (32)$$

where M is total number of alternatives; N is total number of criteria.

Step 9: Calculating rating of all alternatives. The rating of alternative i can be computed by using Closeness Coefficient (CC_i), as illustrated in Equation (33).

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-}, i = 1, 2, 3, \dots, M \quad (33)$$

Step 10: Determining ranking order of each alternative. The highest CC stands for the highest ratings for the alternative (Wang & Lee, 2009). For example, if $CC_A > CC_B$, then $A_A > A_B$. Therefore, the A_A is the best alternative, and A_A will be selected.

2.6.1.3 Fuzzy Analytic Network Process (F-ANP)

F-ANP is the extended form of AHP (Saaty, 1996). F-ANP is generalization of F-AHP that extending the calculation process of AHP by adding the super matrix concept into AHP (Saaty, 1996), meanwhile, integrating fuzzy set theory into pair-wise crisp matrix in AHP. Generally, the basic idea of ANP is similar to AHP that both use pair-wise comparison to

access the relative important of alternative and criteria, and provides a decision-making engine or apparatus for decision-making problem based on the pair-wise comparison. The main difference of ANP from AHP is it models the decision-making problem into network structure instead of hierarchical structure. Saaty (1996) had stated that network structure allows ANP to solve the interaction, dependence and feedback problem that cannot be solved in AHP. This is because the network (feedback) structure does not model the problem into linear top to bottom of hierarchical structure, but components or criteria can loop connecting or cycle connecting (Saaty, 1996) among each other, as illustrated in Figure 2.8.

According to Büyüközkan and Çifçi (2012), F-ANP can perform interrelationships among the decision criteria and requirements in the general form. From a different perspective, it is a network system that can substitute the single direction relationship with dependence and feedback. It uses ratio scale measurements which is based on the pair-wise comparison like AHP (Büyüközkan & Çifçi, 2012). Using F-ANP is not restricted to hierarchical structure, but the criteria and attributes in alternative are independent from each other. This can solve the decision problem which cannot be organized in the hierarchy structure form (Büyüközkan & Çifçi, 2012). One of the examples is from Rezaeiniya, Ghadikolaie, Tekmeh, and Rezaeiniya, 2014. They implemented F-ANP in solving the green house selection problem in Iran. Figure 2.8 shows the simplest structure of F-ANP which is adapted from Büyüközkan and Çifçi (2012).

The steps of F-ANP (Rezaeiniya et al., 2014) are demonstrated as following:

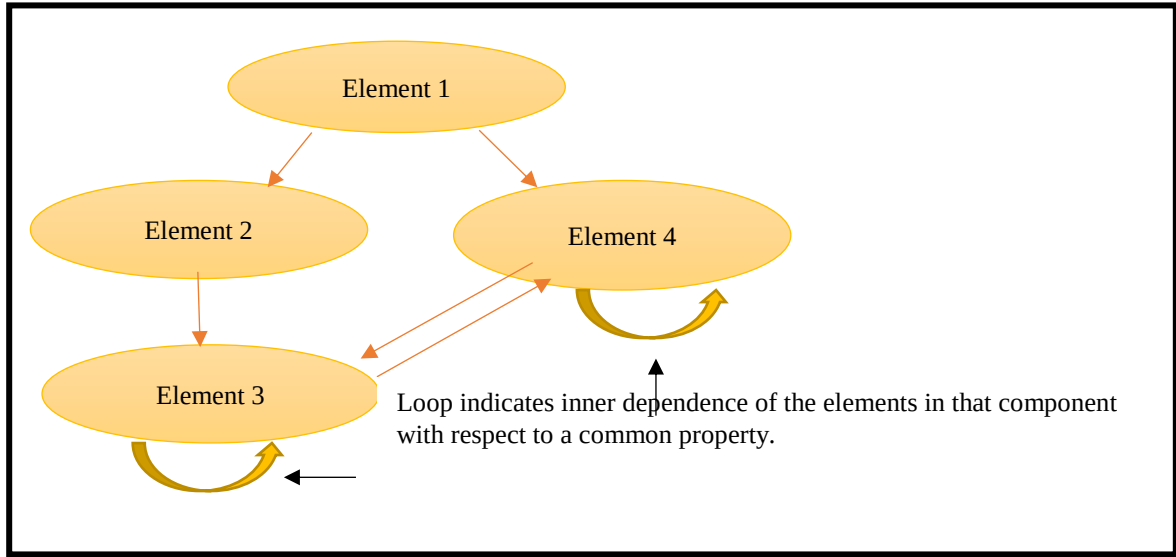


Figure 2.8: The simplest structure of F-ANP (Büyüközkan & Çifçi, 2012).

Step 1: Construct the network structure. In this step, objective and evaluation factors for the decision-making process is determined by DM group. A network pattern is constructed regarding the relationship among the criteria. This direct relationship among the criteria is constructed based on the normal hierarchical structure in F-AHP, as shown in Figure 2.5 whereas, indirect relationship such as the criteria must flow through another criterion is constructed based on network structure, as illustrated in Figure 2.8.

Step 2: Construct pair-wise fuzzy comparison matrix for criteria. In this step, a pair-wise fuzzy comparison matrix is constructed based on the relative weight of each criterion with respect to the main objective of the decision-making problem. The relative weight of each criterion is determined by DM groups without the numerical judgement but the linguistic terms are applied to the pair-wise comparison as demonstrated in Table 2.6. There

are N number of criteria, the pair-wise comparison of criterion i with criterion j generate a square matrix $A_{1N \times N}$, where a_{ij} implies the relative weight of criterion i with respect to criterion j . Pair-wise comparison matrix is constructed in a positive reciprocal matrix format as illustrated in Equation (15).

Step 3: Calculate relative fuzzy normalized weight for each criterion (W_i). In this step, the Chang's extent analysis method (Chang, 1996) is applied to normalize the pair-wise fuzzy decision matrix. The steps of extent analysis method (Chang, 1996) are following:

(a) Define the value of fuzzy synthetic extend. The standard fuzzy arithmetic, as shown in Equation (34) to define the value of fuzzy synthetic extend (S_i) (Chang, 1996). Fuzzy addition operation of m extent analysis value can be used to compute $\sum_{j=1}^m M_i^j$ by using Equation (35) (Chang D. Y., 1996). Meanwhile, $\sum_{i=1}^n \sum_{j=1}^m M_i^j$ is computed by fuzzy addition operation, as shown in Equation (36). The inverse of vector $([\sum_{i=1}^n \sum_{j=1}^m M_i^j]^{-1})$ is computed as illustrated in Equation (37).

$$S_i = \sum_{j=1}^m M_i^j \otimes [\sum_{i=1}^n \sum_{j=1}^m M_i^j]^{-1} \quad (34)$$

where M_i^j refers to the extent analysis score for criterion i based on object j .

$$\sum_{j=1}^m M_i^j = (\sum_{j=1}^m a_i^j, \sum_{j=1}^m b_i^j, \sum_{j=1}^m c_i^j) \quad (35)$$

$$\sum_{i=1}^n \sum_{j=1}^m M_i^j = (\sum_{i=1}^n a_i^j, \sum_{i=1}^n b_i^j, \sum_{i=1}^n c_i^j) \quad (36)$$

$$[\sum_{i=1}^n \sum_{j=1}^m M_i^j]^{-1} = \left(\frac{1}{\sum_{i=1}^n c_i}, \frac{1}{\sum_{i=1}^n b_i}, \frac{1}{\sum_{i=1}^n a_i} \right) \quad (37)$$

where n and m are total number of criteria.

(b) The degree of possibility between two criteria ($M_1 \geq M_2$) is computed as shown in Equation (38) (Chang, 1996). Based on Equation (38), it can be interpreted into Equation (39) (Chang, 1996).

$$V(M_1 \geq M_2) = \text{Sup}[\min(\mu_{M_1}(X), \mu_{M_2}(Y))] \quad (38)$$

where $M_1 = (l_1, m_1, u_1)$; $M_2 = (l_2, m_2, u_2)$.

$$V(M_1 \geq M_2) = \text{hgt}(M_2 \cap M_1) = \mu_{M_1}(x) \begin{cases} 1, \text{ if } m_1 \geq m_2 \\ 2, \text{ if } l_2 \geq u_1 \\ \frac{u_2 - l_1}{(u_1 - l_2) - (m_2 - m_1)} \text{ else} \end{cases} \quad (39)$$

where x indicates the coordinate of the supreme intersection point of X between two criteria M_1 and M_2 .

(c) The degree of possibility for a convex fuzzy number, $M_a, a = 1, 2, 3, \dots, d$, it can be computed in Equation (40) (Chang, 1996).

$$V(M \geq M_1, M_2, M_3, \dots, M_d) = V(M_1 \geq M_2), \dots, V(M_1 \geq M_d) \quad (40)$$

where , $a = 1, 2, \dots, d$ and d is whole number of experts in DM groups

(d) The weight indices in pair-wise fuzzy decision matrix can be shown in Equation (41), and it can be used to compute the weight vectors as shown in Equation (42) (Chang, 1996).

$$w^-(A_i) = \min V(S_i \geq S_{dm}), dm = 1, 2, 3, \dots, k, dm \neq i \quad (41)$$

where k is total number of experts in DM groups

$$WV^-(X_i) = [w^-(A_1), w^-(A_2), w^-(A_3), \dots, w^-(A_n)]^T, i = 1, 2, 3, \dots, n \quad (42)$$

where n is total number of criteria.

(e) Normalization of weight vector by using Equation (43)

$$W_i = \frac{WV(X_i)}{\sum_{i=1}^n WV(X_i)}, i = 1, 2, 3, \dots, n \quad (43)$$

where n is total number of criteria; W is non fuzzy number (Chang, 1996).

Step 4: Constructing the weighted super matrix. In this step, a weighted super matrix is constructed based on all the relationship between all criteria and the weight result from Equation (43), as shown in Equation (44) (Saaty, 1996).

$$W_i = \begin{matrix} C \\ C_1 \\ \vdots \\ C_N \end{matrix} \begin{bmatrix} C_1 & \dots & C_N \\ 0 & \dots & w_{1N} \\ \vdots & \ddots & \vdots \\ w_{1N} & \dots & w_{3N} \end{bmatrix} \quad (44)$$

where N is total number of criteria.

Step 5: Constructing the limit super matrix. A limit matrix is constructed based on Markov's equation (Kapliński & Tamošaitiene, 2010), as shown in Equation (45). Power of weighted super matrix is calculated until consecutive powers are the same from two criteria, such as $i = k$.

$$\text{limit super matrix} = (\text{weighted super matrix})^{2k+1} \quad (45)$$

where k is consecutive power when $i = k$.

Step 6: Aggregation. In this step, the alternative who owns the top value in limit super matrix is chosen as the best alternative (Rezaeiniya et al., 2014). Limit matrix lists all alternative value by using Equation (45). Limit matrix plays important in ANP as it clearly shows the relationship among two criteria for an alternative. From other perspective, limit matrix shows which criterion affect another criterion by showing the relative weights between both criteria.

2.6.1.4 Fuzzy VIKOR (F-VIKOR)

Visekriterijumska optimizacija I KOmpromisno Resenje (VIKOR) is developed by Opricovic in 1998 (Opricovic, 2011). VIKOR is mainly designed to solve the ranking and choosing the best alternative from a group of alternatives, meanwhile, defining the best compromise solution for multiple contradicting or conflicting criteria decision problem (Rostamzadeh, Govinda, Esmaeili, & Sabaghi, 2015). The compromise solution refers to reconcile method that has the closest distance to ideal solution (Opricovic, 2011). Generally, the logic behind of F-VIKOR algorithm is based on maximum group benefit (majority rule) and fuzzy worst value for listing and selecting of best alternative. From other perspective, F-VIKOR implements fuzzy set theory, and aggregated fuzzy merit (Q) to imply the distance between alternative to ideal solutions (Opricovic, 2011). One of the examples application of F-VIKOR is by Alguliyev, Aliguliyev, and Mahmudova (2015) which applied it for personnel selection problem. Figure 2.9 shows the general steps in F-VIKOR. The general steps of F-VIKOR (Alguliyev et al., 2015) are demonstrated in the following:

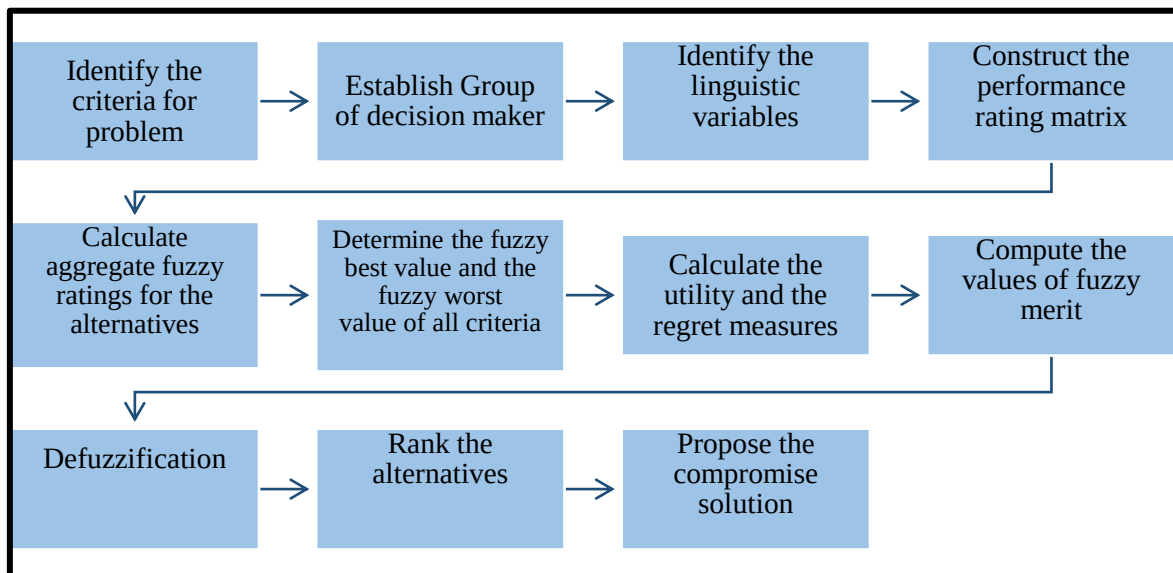


Figure 2.9: The general steps in F-VIKOR (Alguliyev et al., 2015).

Step 1: Identification of criteria & Forming DM group. A group of k number of experts is formed into DM group. The criteria that are needed for decision-making process are defined by DM group based on their own knowledge and expertise. For example, working experience, education background and personality traits are the criteria for job recruitment problem.

Step 2: Constructing performance matrix for alternative. A $m \times n$ performance matrix for m numbers of alternative and n number of criteria is formed based on the linguistic terms as shown in Table 2.7. A typical format of performance matrix for alternative can be illustrated in Equation (22).

Step 3: Calculating aggregated fuzzy ratings for alternative. Aggregated fuzzy rating, $\tilde{x}_{ijk} = (x_{ijk}^l, x_{ijk}^m, x_{ijk}^u)$ for alternative i with respect to criterion y which is assigned by expert k can be computed in Equation (46).

$$\tilde{x}_{ijk} = \left(\frac{1}{k} \sum_{k=1}^K x_{ijk}^l, \frac{1}{k} \sum_{k=1}^K x_{ijk}^m, \frac{1}{k} \sum_{k=1}^K x_{ijk}^u \right) \quad k = 1, 2, 3, \dots, K \quad (46)$$

where K is total number of criteria.

Step 4: Determine the fuzzy best value and fuzzy worst value for all criteria. The fuzzy best value or the fuzzy positive ideal solution, x_j^+ stands for the ideal result for criterion j which is computed in Equation (47) (Alguliyev et al., 2015). The fuzzy worst value or fuzzy negative ideal solution, x_j^- is the worst score for criterion j can be calculated in Equation (48) (Alguliyev et al., 2015).

$$x_j^+ = \begin{cases} \max_{i=1,2,3,\dots,k} \{\tilde{x}_{ij}\}, & \text{for benefit criterion} \\ \min_{i=1,2,3,\dots,k} \{\tilde{x}_{ij}\}, & \text{for negative criterion} \end{cases} \quad (47)$$

$$x_j^- = \begin{cases} \min_{i=1,2,3,\dots,k} \{\tilde{x}_{ij}\}, & \text{for benefit criterion} \\ \max_{i=1,2,3,\dots,k} \{\tilde{x}_{ij}\}, & \text{for negative criterion} \end{cases} \quad (48)$$

where the higher score for benefit criteria indicates the higher benefit can bring to decision-making, such as education background in job recruitment problem; the higher score for negative criteria implies the less benefit can bring to decision-making, for instance, cost to hire job applicants in job recruitment problem; K is total number of criteria;

Step 5: Calculating utility and regret measure for each alternative. F-VIKOR uses preference of alternative with respect to each ideal solution to indicate the ranking of alternative (Opricovic, 2011). F-VIKOR calculates utility, $\tilde{S}_i$ and regret measure, $\tilde{R}_i$ for ranking candidate i by using compromise programming method (Alguliyev et al., 2015), as illustrated in Equation (49) and (50) respectively.

$$\tilde{S}_i = \sum_{j=1}^m \left| \frac{\tilde{w}_j(\tilde{x}_j^+ - \tilde{x}_{ij})}{(\tilde{x}_j^+ - \tilde{x}_j^-)} \right|, i = 1, 2, 3, \dots, n \quad (49)$$

$$\tilde{R}_i = \max_{j=1,\dots,m} \left| \frac{\tilde{w}_j(\tilde{x}_j^+ - \tilde{x}_{ij})}{(\tilde{x}_j^+ - \tilde{x}_j^-)} \right|, i = 1, 2, 3, \dots, n \quad (50)$$

where $\tilde{w}_j$ is the fuzzy weight for criterion j ; n is total number of alternatives;

Step 6: Calculating fuzzy merit for each alternative. F-VIKOR calculate aggregated fuzzy merit $\tilde{Q}_i$ imply the distance between alternative i to ideal solutions (Opricovic, 2011). Equation (51) demonstrates the fuzzy merit for alternative i (Alguliyev et al., 2015).

$$\tilde{Q}_i = \lambda \frac{\tilde{S}_i - \tilde{S}^-}{\tilde{S}^+ - \tilde{S}^-} + (1 - \lambda) \frac{\tilde{R}_i - \tilde{R}^-}{\tilde{R}^+ - \tilde{R}^-}, i = 1, 2, \dots, n \quad (51)$$

where n is total number of alternatives; $\tilde{S}$ belongs to maximum group utility,

$$\tilde{S}^+ = \max_{i=1,2,3,\dots,k} \{\tilde{S}_i\} \text{ and } \tilde{S}^- = \min_{i=1,2,3,\dots,k} \{\tilde{S}_i\}; \tilde{R} \text{ belongs to minimum regret measure, } \tilde{R}^+ = \max_{i=1,2,3,\dots,k} \{\tilde{R}_i\} \text{ and } \tilde{R}^- = \min_{i=1,2,3,\dots,k} \{\tilde{R}_i\}; \lambda \in [0,1].$$

Step 7: Defuzzification. By using defuzzification method (Lee, 1990), as shown in Equation

(52), triangular fuzzy number of $\tilde{S}$, $\tilde{R}$ and $\tilde{Q}$ can be transformed into crisp number, as illustrated as Equations (53), (54) and (55) respectively.

$$A = \frac{(a^l + a^m + a^u)}{3}, i = 1, 2, \dots, n \quad (52)$$

$$S_i = \frac{(s_i^l + s_i^m + s_i^u)}{3}, i = 1, 2, \dots, n \quad (53)$$

$$R_i = \frac{(r_i^l + r_i^m + r_i^u)}{3}, i = 1, 2, \dots, n \quad (54)$$

$$Q_i = \frac{(q_i^l + q_i^m + q_i^u)}{3}, i = 1, 2, \dots, n \quad (55)$$

where n is total number of alternatives;

Step 8: Rank alternatives. All the alternatives are sorting in ascending order based on fuzzy merit Q value. The smaller the fuzzy merit Q value, the better the alternative (Alguliyev et al., 2015). Therefore, the alternative who owns the smallest fuzzy merit Q value is considered as the best alternative.

Step 9: Proposing compromise solution for decision-making problem. In this step, the minimum of fuzzy merit Q value (fuzzy merit of best alternative) which is obtain from Equation (51) is considered as the compromise solution for decision-making problem, if and only if fuzzy merit Q value of best alternative achieves two conditions below:

(a) Acceptable advantage is applied to check is the real best alternative that can bring more advantage for decision-making problem, by using Equation (56) (Alguliyev et al., 2015).

$$\frac{(\tilde{Q}_{A_2} - \tilde{Q}_{A_1})}{\tilde{Q}_{A_n}} - \tilde{Q}_{A_1} \geq \frac{1}{n-1} \quad (56)$$

where $\tilde{Q}_{A_1}$ is fuzzy merit of best alternative; $\tilde{Q}_{A_2}$ is the second position of alternative in ranking list; n is the total number of alternatives.

(b) Acceptable stability is implemented to check is best alternative has the best maximum group utility which is computed from Equation (49) and minimum regret measure which is obtain from Equation (50) (Alguliyev et al., 2015).

2.6.1.5 Fuzzy ELECTRE (F-ELECTRE)

F-ELECTRE stands for Fuzzy Elimination Et Choix Tradiosant la REaite (Rouyendegh & Erkan, 2013). The fundamental idea of F-ELECTRE is based on concordance and discordance index of criteria to rank and recommend the best alternative (Rouyendegh & Erkan, 2013). Concordance and discordance index are used for calculating all different weight of criteria for alternative. Concordance index aims to find which alternative is better than another alternative (Raoot & Rakshit, 1993), and discordance index uses to find which

alternative is worse than another alternative (Montazer, Saremi, & Ramezani, 2009). One of the example application of F-ELECTRE is by Rouyendegh and Erkan (2013). They implement F-ELECTRE in academic staff selection. Figure 2.10 shows the general steps in F-ELECTRE which is adapted from Rouyendegh and Erkan (2013).

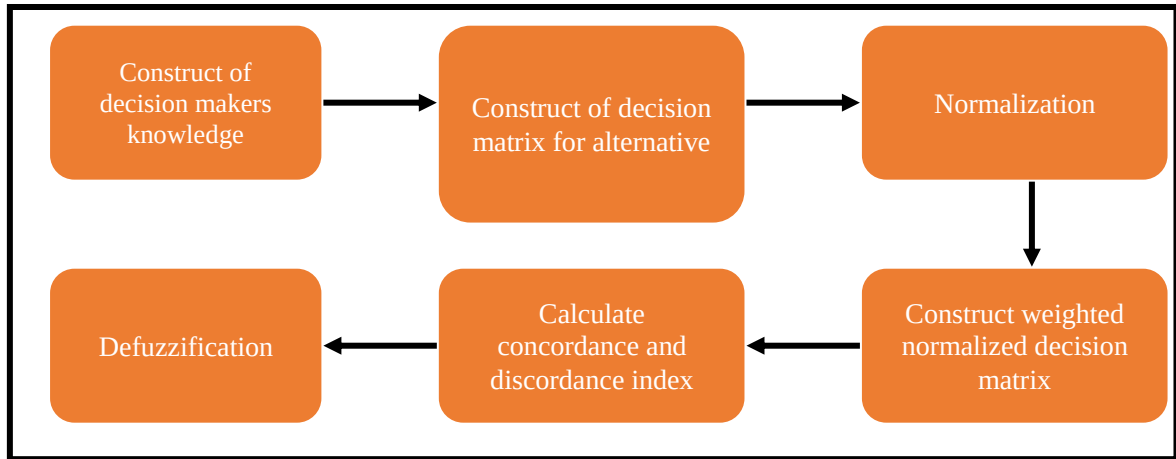


Figure 2.10: The general steps in F-ELECTRE (Rouyendegh & Erkan, 2013).

The general steps of F-ELECTRE (Rouyendegh & Erkan, 2013) are illustrated in the following:

Step 1: Identification of criteria & Forming DM group. A group of k number of experts is formed into DM group. The criteria that are needed for decision-making process are defined by DM group based on their own knowledge and expertise. For example, working experience, education background and personality traits are the criteria for job recruitment problem.

Step 2: Constructing decision matrix for alternative. A $m \times n$ performance matrix for m numbers of alternative and n number of criteria is formed based on the linguistic terms as

shown in Table 2.7. A typical format of performance matrix for alternative can be illustrated in Equation (22).

Step 3: Constructing normalized decision matrix for alternative. Decision matrix for alternative is normalized by using Equation (57) and (58) (Rouyendegh & Erkan, 2013). Equation (59) illustrates a normalized decision matrix for alternative.

$$r_{ij}^+ = \frac{\tilde{x}_{ij}}{\sqrt{\sum_{i=1}^m (\tilde{x}_{ij})^2}} \quad (57)$$

$$r_{ij}^- = \frac{1/\tilde{x}_{ij}}{\sqrt{\sum_{i=1}^m (1/\tilde{x}_{ij})^2}} \quad (58)$$

where r_{ij}^+ is maximization criteria that can bring to decision-making, such as education background in job recruitment problem; r_{ij}^- is the minimization criteria that imply the less benefit can bring to decision-making, for instance, cost to hire job applicants in job recruitment problem; m is total number of criteria;

$$X = \begin{pmatrix} r_{11} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mn} \end{pmatrix} \quad (59)$$

where n is total number of alternatives; m is total number of criteria.

Step 4: Constructing weighted normalized decision matrix for alternative. Weighted normalized decision matrix for alternative is computed by multiplication of importance weight of criteria to normalized decision matrix of alternative by using Equation (60) (Rouyendegh & Erkan, 2013).

$$\tilde{v}_{ij} = r_{ij} \times \tilde{w}_{ij}, i = 1, 2, \dots, n; j = 1, 2, \dots, m \quad (60)$$

where n indicates total sizes of alternatives; m is total number of criteria.

Step 5: Calculating concordance and discordance indexes for each criteria. The concordance index is computed based on Equation (61) (Raoot & Rakshit, 1993), and discordance index is calculated based on Equation (62) (Montazer, Saremi, & Ramezani, 2009).

$$C_{pq} = \begin{cases} c_{pg}^l = \sum_{j=1}^m w_j^l \\ c_{pg}^m = \sum_{j=1}^m w_j^m \\ c_{pg}^u = \sum_{j=1}^m w_j^u \end{cases} \quad (61)$$

where m is total number of criteria; $C_{pq} (c_{pg}^l, c_{pg}^m, c_{pg}^u)$ is the degree of confidence in pair-wise judgement to compare the alternative p and alternative q (Raoot & Rakshit, 1993).

$$D_{pq} = \begin{cases} D_{pq}^l = \frac{\sum_{j^*} |v_{pj^*}^l - v_{qj^*}^l|}{\sum_j |v_{pj}^l - v_{qj}^l|} \\ D_{pq}^m = \frac{\sum_{j^*} |v_{pj^*}^m - v_{qj^*}^m|}{\sum_j |v_{pj}^m - v_{qj}^m|} \\ D_{pq}^u = \frac{\sum_{j^*} |v_{pj^*}^u - v_{qj^*}^u|}{\sum_j |v_{pj}^u - v_{qj}^u|} \end{cases} \quad (62)$$

where m is total number of criteria; $D_{pq} (D_{pg}^l, D_{pg}^m, D_{pg}^u)$ is the degree of disagreement in pair-wise judgement to compare the alternative p and alternative q (Montazer et al., 2009); j^* indicates all the criteria; v_{ij} represents the normalized weighted of alternative i based on criterion j .

Step 6: Defuzzification. Both concordance and discordance indexes need to be defuzzified by using Equation (63) and (64) respectively (Rouyendegh & Erkan, 2013). After

defuzzification of both concordance and discordance indexes, the outranking of alternative p and q is drawn by alternative p is better than alternative q , if concordance index of alternative p is greater than alternative q , and the discordance index of alternative p is lower than alternative q . Therefore, alternative who owns the greater concordance index but lower discordance index, is considered better, compared to its opponent alternative.

$$C_{pq}^* = \sqrt[Z]{\prod_{z=1}^Z C_{pq}^Z} \quad (63)$$

$$D_{pq}^* = \sqrt[Z]{\prod_{z=1}^Z D_{pq}^Z} \quad (64)$$

where Z is 3, if fuzzy triangular fuzzy membership function is applied.

2.6.1.6 Hamming Distance Method

Hamming distance algorithm is first proposed by Richard Hamming in 1950 (as cited in Lesnard, 2010). The logic behind of hamming distance algorithm is to calculate the distance between best alternative and other alternatives (Md Saad et al., 2014). The best alternative is the alternative whose values of criteria are as near as possible to best values of criteria. Hamming distance performs distance calculate between two strings of equal lengths (Lesnard, 2010). Generally, it calculates distance between two sequences which have equal lengths. In hamming distance, two strings of equal lengths indicate vectors over finite field (Lesnard, 2010).

From other perspective, the alternative with the minimum distance values from the ideal values is likely to be chosen as the potential alternative. Nevertheless, if the distance among the candidates are the same, hamming distance method faces a problem to rank among them (Md Saad et al., 2014). One of the examples of using hamming distance method is by Md

Saad et al. (2014). They integrated fuzzy set theory into hamming distance method to solve personnel selection problem. Figure 2.11 shows the general steps in hamming distance method which is adapted from Md Saad et al. (2014).

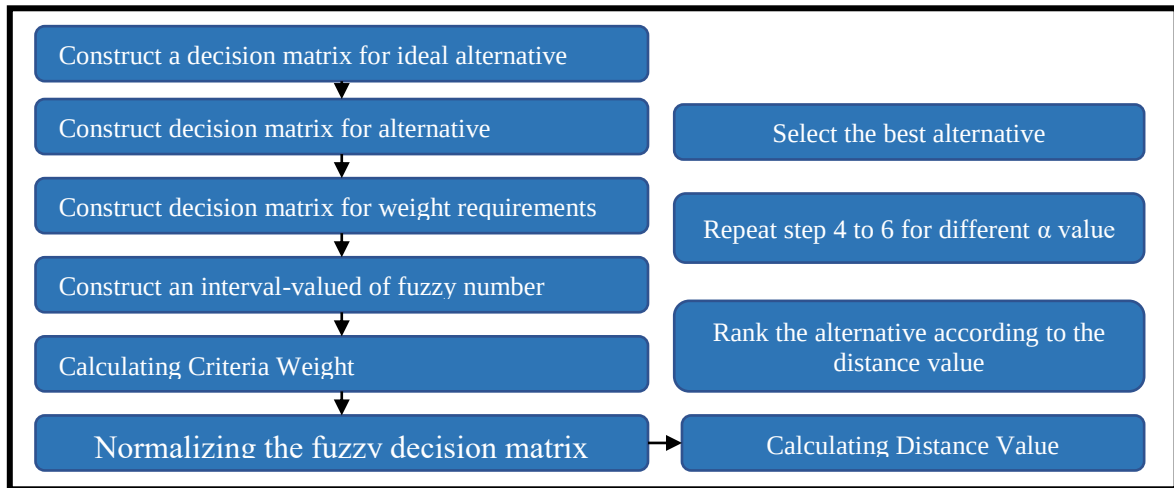


Figure 2.11: The general steps in Hamming Distance which is adapted from Md Saad et al. (2014).

The general steps of hamming distance (Md Saad et al., 2014) are illustrated in the following:

Step 1: Construct the ideal alternative matrix. Ideal alternative matrix is constructed based on the linguistic terms as shown in Table 2.7. All experts from DM group need to come to an agreement in normalizing their own ideal alternatives' values into one final best value for each criterion (Md Saad et al., 2014).

Step 2: Construct the normal decision matrix for all alternative. Decision matrix for all alternative is constructed based on the linguistic variables which assigned by decision groups, as shown in Table 2.7.

Step 3: Construct the fuzzy weight matrix for all criteria. Importance to criteria are assigned by DM group, based on fuzzy linguistic terms, as illustrated in Table 2.6.

Step 4: Construct an interval-valued fuzzy number. The interval-valued fuzzy number is constructed by α -cut of triangular fuzzy number which is illustrated in equation (65).

$$[A]_{\alpha} = [\alpha_1 + \alpha(\alpha_2 - \alpha_1), \alpha_3 - \alpha(\alpha_3 - \alpha_2)], \alpha \in (0,1] \quad (65)$$

where $\alpha \in [0,1]$.

Step 5: Normalization of Fuzzy Weight. Projection value P_{ij} is obtained from the equation (66). A projection matrix is constructed based on each projection value.

$$P_{ij} = \frac{W_{ij}}{\sum_{i=1}^m W_{ij}} \quad (66)$$

where W_{ij} is the weight for criterion i ; m is the total number of criteria.

Step 6: Calculate both subjective and objective weight. Subjective weighting method is to determine the decision groups' weights for each criterion (Wang & Lee, 2009). The formula subjective weighting described in Equation (67) (Md Saad et al., 2014).

$$\tilde{W}_j = \frac{1}{n} (\sum_{j=1}^n w_j^e), j = 1, 2, 3, \dots, n \quad (67)$$

According to Wang and Lee (2009), entropy-based objective weighting method extends Shannon's concept which applies entropy measure to calculate the objective weight. The entropy weight mainly uses to determine the differences candidates approaches to one another in terms of each criterion. The larger the entropy value, the smaller the entropy weight. Firstly, the interval valued fuzzy number needs to be transformed into crisp number in Equation (68) (Chaghooshi, Fathi, & Kashef, 2012) with the α -cut of triangular fuzzy

number in Equation (65) (Md Saad et al., 2014) before applied the Shannon's entropy algorithm. Next, fuzzy weight matrix can be normalized in order to get the projection value for each criterion, P_{ij} , in Equation (66) (Wang & Lee, 2009). After that, entropy values can be calculated in Equation (69) (Wang & Lee, 2009) after project value for each criterion is calculated.

$$W_{ij} = \frac{(w_{ij}^l + w_{ij}^u)}{2} \quad (68)$$

$$e_j = -k \sum_{j=1}^n P_{ij} \ln P_{ij} \quad (69)$$

where k is a constant, let $k = (\ln(m))^{-1}$.

The degree of divergence d_i of the inherent data of each criterion $C_j (j = 1, 2, \dots, n)$ is calculated in Equation (70) (Wang & Lee, 2009). The degree of divergence shows the intrinsic contrast intensity divergence c_i . The higher the d_i , the more important for the criterion, c_i . The objective weight can be calculated in Equation (71) (Wang & Lee, 2009).

$$d_j = 1 - e_j \quad (70)$$

$$W_j = \frac{d_j}{\sum_{k=1}^n d_k} \quad (71)$$

where k is a constant, let $k = (\ln(m))^{-1}$.

Step 7: Calculate distance values between the best alternative with each alternative.

Each distance between the best alternative with each alternative is calculated based on the

subjective weight which is illustrated in equation (72), and objective weight which is presented in equation (73) (Md Saad et al., 2014).

$$d_{NHD}(R, S) = \frac{1}{2n} (\sum_{j=1}^n (|r_j^L - s_{ij}^L| + |r_j^U - s_{ij}^U|)) \quad (72)$$

$$d_{WHD}(I, D) = \sum_{j=1}^n (w_j |v_j^L - x_j^L| + w_j |v_j^U - x_j^U|) \quad (73)$$

Step 8: Rank the alternative based on the distance obtained from step 7. The alternatives are ranked in ascending order based on the distance results from step 7. Therefore, the alternative with the shortest distance is the best alternative which is going to be recommended for the multiple criteria decision problem.

2.6.2 Comparison of Fuzzy Multiple Criteria Decision-making (FMCDM)

There are many FMCDM have been proposed in last few years. The fundamental concept of FMCDM is to implement fuzzy set theory into their own MCDM algorithm, by changing the crisp values which are implemented to define the importance weights of criteria and ratings of alternatives into fuzzy membership function, for instance triangular fuzzy membership function and trapezium membership function. All FMCDM need to perform the complex computational processes because there are many layers to calculate the result for a decision. Moreover, counterintuitive outcomes occur in certain situation which cannot get the realistic decision (Ertuğrul & Karakaşoğlu, 2008). From other perspective, there is no one best FMCDM that is able to solve all kinds of different multiple criteria decision-making problems. Therefore, there are many FMCDM have been proposed for solving different multi-criteria decision-making problems. There are 6 techniques of FMCDM which have mentioned above. Here are some comparisons between them.

F-AHP requires the more complex computation than other FMCDMs like F-TOPSIS and hamming distance method. This is because all the problem need to be organized in the hierarchical structure before other steps proceed. Therefore, decision problem with more criteria needs to make more levels in hierarchical structure. This directly brings more computation processes before the result is reached.

Pair-wise comparison for preferable criteria and attributes are constructed in F-AHP and F-ANP only. Other FMCDM like F-TOPSIS, F-VIKOR and hamming distance method do not need pair-wise comparison. Even both F-AHP and F-ANP are using the same pair-wise comparison for criteria by using positive reciprocal matrix format as illustrated in Equation (15), they are difference on the way alternatives are ranked. F-AHP calculates global priorities ($\tilde{S}_i$) of candidate i by synthesizing local priorities across all the criteria from pair-wise comparison matrix of criteria to rank the candidate, as shown in Equation (19) (Varmazyar & Nouri, 2014). On the other hand, F-ANP computes the limit super matrix by using Markov's equation (Kapliński & Tamošaitiene, 2010), as shown in Equation (45) to rank the candidate. Apart from ranking of candidate, there is another difference between F-AHP and F-ANP in problem modelling. F-ANP is the extended form of AHP (Saaty, 1996). It does not execute a strict hierarchical structure like F-AHP because it is using the system with feedback method. This allows F-ANP to execute the loop indicates the inner dependence of element within a component. In other words, F-ANP uses a network which does not require specifying levels as in a hierarchical structure.

Distance-based solution is one of the famous MCDM techniques in solving FMCDM problem. F-TOPSIS, F-VIKOR and hamming distance method utilizes the distance

calculation concept in the ranking process. Nevertheless, there is a difference between these three FMCDMs. F-VIKOR uses the aggregate fuzzy merit function to represent the distance of alternative to ideal solution. F-TOPSIS calculate the distance from PIS to PNS to rank the alternatives based on strings values whereas hamming distance method only can perform the distance calculation between two strings of equal length. Therefore, an interval-valued of fuzzy numbers of each candidate need to be constructed in hamming distance method but it is not needed in F-TOPSIS. Hamming distance method is hard to rank the candidates when the distance among the candidates are the same (Md Saad et al., 2014), but this can be avoided in F-TOPSIS.

2.7 Kansei Engineering Model

Kansei is the Japanese word which can describe as personal's subjective feelings from a particular artefact, surroundings or circumstance implantation of each senses (Nagamachi, 1995). The senses included vision, smell, hearing, taste, recognition and sense of equilibrium. According to Yoshimura and Papalambros (2004), Kansei is the receptivity of a sense receptor where feeling stimulated by stimuli from environment. Furthermore, Lokman (2010) stated that Kansei is the consequence of perception and five senses. In short, it is an unconscious psychological process which acts as high level of process in the brain. The progression of Kansei starts with collecting the sensory inputs, for instance sensation, sentiment and instinct, through the medium of each human sense (Lokman, 2010). Figure 2.12 shows the progression of Kansei which is adapted from Lokman and Nagamachi (2010).

When the stimuli are stimulated by the receptor of the sensory organ, sensation, feelings, consciousness and memory will appear (Lokman, 2010). Due to unconsciousness,

progression of Kansei cannot be estimated straightly. It is because people can only observe the outcomes and results of progression of Kansei but not the Kansei itself (Lokman, 2010). Therefore, it concludes that Kansei can only be estimated indirectly through sensory organs. Apart from that, Kansei can estimate by evaluating on influence of sensation stimulation on human brain activity (Lokman, 2010). Human emotion reaction can be measured by identifying how input signals can affect brain activity (Shafieyoun & Maiocchi, 2014). For instance, it can measure based on heart beat rate, electroencephalography, electromyography, facial expression, and functional magnetic resonance imaging technology.

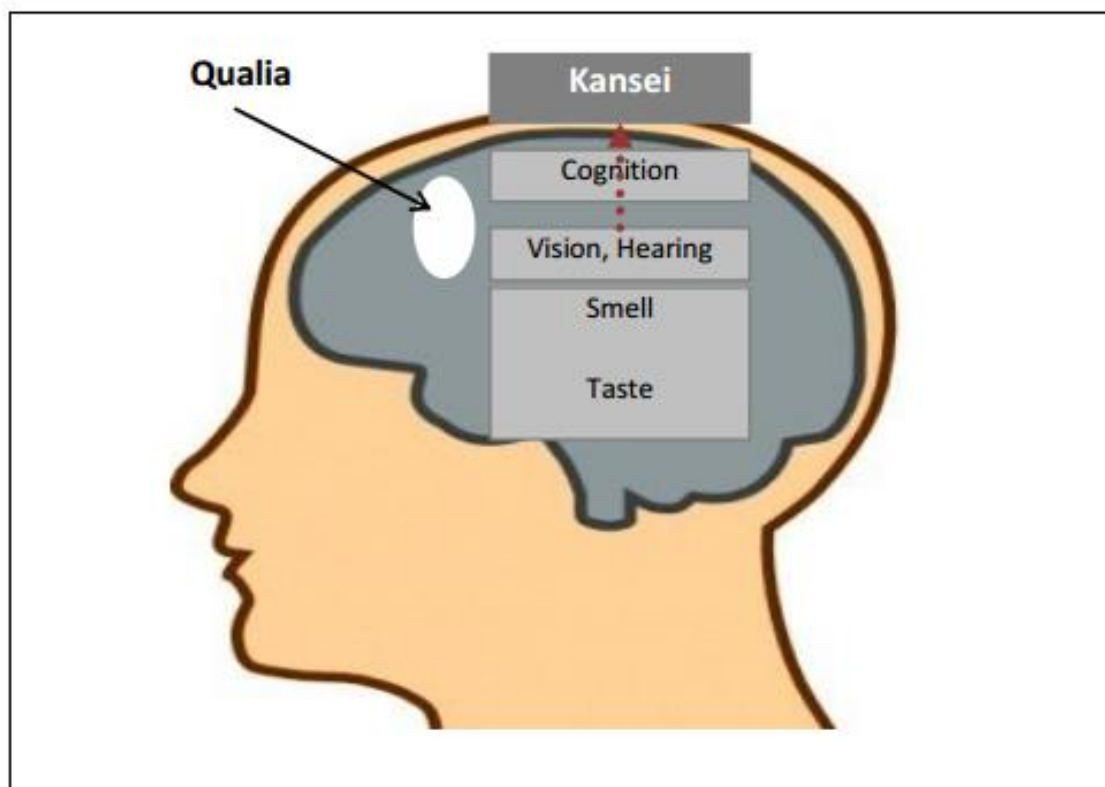


Figure 2.12: The progression of Kansei which is adapted from Lokman and Nagamachi (2010).

2.7.1 Kansei Engineering (KE)

Kansei Engineering (KE) is the technique that combines Kansei which stands for sensations, emotions and feelings by the engineering methodology (Shafieyoun & Maiocchi, 2014). Next, it is also a method to translate human feelings and emotions into design of product (Schütte , 2005). It is an area which is conducted technologically in designing the products that are able to bring the contentment and happiness to user. It can analyse human Kansei, and integrate them together into design of product (Lokman, 2010). The word Kansei in KE is narrower than the actual implication. Hence, KE is the technology that combine the users' feelings and emotions in designing a new product.

In KE, the most important term is the Kansei Words (KW). KW is the term to describe and express the human Kansei in text when they encountered the stimulation by the object product (Lokman, 2010). In short, KW uses to define human Kansei to particular product, object and environment. Lokman and Nagamachi (2010) had stated that KW can be in the format of adjective, nouns and a short sentence to describe the product, object, or environment.

Nowadays, the development of product trends shows that the success of a product in the market is determined by the inclusion of users' demands toward the technical characteristics of design of product (Lokman, 2010). Even the definite requirement is easy to define, the implicit demands like feelings and emotions are hard to measure. Therefore, many countries have been employing KE in product design methodology. For example, in Japan Mazda Automobile company implemented KE in Miyata model (Yamamoto, 1986), Italy Fiat Automobile company also applies KE in their car design (Wang, Liu, & Wu, 2011). In

America, the Ford Automobile company employs the KE in its new family of car models (Nagamachi & Lokman, 2016). In Korea, Hyundai Automobile company and Samsung Electronics also implemented the KE in their product design (Nagamachi & Lokman, 2016).

Japan is a developed country which always leads the world in developing the innovating product. One of the most significant example of KE use in Japan is by Mazda Company. It implemented KE in designing the Miyata model (Yamamoto, 1986). Next, Sharp LCD display applied KE in conventional ocular, and Wacol had used KE in designing the underwear to enhance their sales in competitive market (Schütte , 2005).

Apart from that, KE has been used in design of various consumer products. For instance, Kumar and Karla (2013) had applied the KE in evaluation of door handles design. They used the regression model to calculate the KE. This method can link the users' demands, and design description together easily. Therefore, it is easy for designers to get the most significant demands in designing the product (Kumar & Karla, 2013). Moreover, Andy and Yashmi (2014) had used KE in designing the urban area in order to overcome the aging problem in Iran. They used 30 KWs which were related to elders' demands. Recognition and understanding of elders' demands are the main purpose of using KE for them to get the actual requirements for elders (Andy & Yashmi, 2014). With the KE, quality of elders' life had been improving in Iran. In addition, Kittidecha, Marasinghe, and Koichi (2016) had implemented KE to tactile sense in the Thai food wrapping materials. They investigated 9 different wrapping materials in Thai food. They calculated the average mean value of the food wrapping samples for evaluation the preferable KW in Thai food wrapping materials.

Their research demonstrated clearly the steps and KE concepts to integrate the human senses to physical object to come out with a new design.

2.7.2 KE Methodology

There are eight KE schemes which are mainly focused on different aspects (Lokman, 2010). KE type I uses for classifying the category. KE type II focuses on KE system. KE type III concentrates on KE modelling which duels with mathematical and logic in system. KE type IV centralize on Hybrid KE. KE type V is called as Virtual KE. It focuses on virtual reality in KE. KE type VI implodes the Collaborative KE. KE type VII focuses on Concurrent KE, and KE type VIII concentrates on Rough Sets KE. From these frameworks, KE type I is the simplest form of KE scheme (Shafieyoun & Maiocchi, 2014). Figure 2.13 shows the standard KE model which is proposed by Schütte (2005).

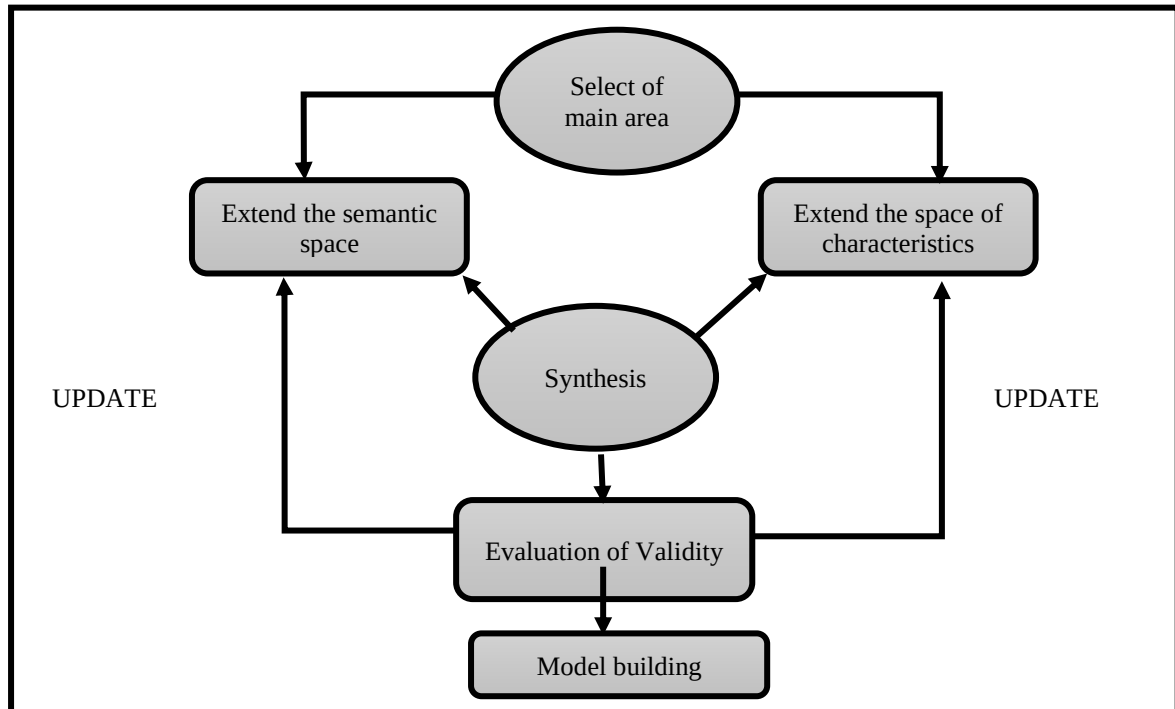


Figure 2.13: Standard KE model which is proposed from Schütte (2005).

There are six main stages in KE model in as shown in Figure 2.13. The first stage is the selection of main area. This stage involves the segmentation of marketing, targeting the group and finding the definition of product (Kumar & Karla, 2013). It needs to choose the objective group, specific to the new product then only starts to collect the product samples which are related to the main area. According to Shafieyoun and Maiocchi (2014), the selection of objective group depends on certain product and market. Selection of target group is important in KE because Kansei experience is distinct with different product (Nagamachi, 1995). Selection of target group can be done by segmentation of target user or expert (Lokman, 2010). With the target group, it enables to gain a better outcome in forming KW. The tasks in this stage are to identify the main area, and do the product samples collection. Product samples can be gathered from internet, market. For instance, the door samples were collected from online catalogues (Kumar & Karla, 2013). All the samples need to undergo screening process before proceeding to the next stage. Kumar and Karla (2013) stated that screening the existing product samples can reduce the load and adjudication by the respondents in further step. The existing product samples are screened based on the similarity of samples, repetitiveness style, and identical features in the product samples. Therefore, the selection of domain focuses on selecting the main product or domain which needs to be inspected.

Measuring of Kansei or collection of KWs is the main task of this extending the semantic spaces (Shafieyoun & Maiocchi, 2014). It is the process of capturing the user's Kansei (Lokman, 2010). Generally, it is the process to collect the adjectives to express the user's emotion toward the product sample. Those samples are categorized into few attributes. The attributes of product samples are the obvious characteristics of the product samples. Then,

different KWs are collected based on the attributes of product samples. Collection of KWs can be obtained by interviewing experts in target group which had defined in selection of main area. For example, the target group is recruiters or human resource manager if the main domain is the job recruitment. Moreover, magazines, internet sources or literature review are other methods of collecting KWs (Shafieyoun & Maiocchi, 2014). Thus, the main task in this stage is to collect both positive and negative KWs which can define the domain that was selected in the previous stage.

After that, extending the space property is similar to extending of semantic space (Shafieyoun & Maiocchi, 2014). Schütte (2005) had stated that the space properties is counterpart of the semantic. It is because both need to undergo collect, select and compile the product samples in order to get the KWs. However, there are significant difference from these two spaces that space properties is to find out the most important properties among the KW. This difference is clearly shown in steps of collection and selection of KWs. Collection of KWs based on the conceal properties of the product such as the material used. Before proceeding to the synthesis stage, merging the both KWs from semantic space and space of properties.

In synthesis stage, semantic spaces and space of properties are combined and linked together to define the KW. For example, the 'bitter' KW are defined by the combination of the color of bottle and the shape of the bottle (Schütte , 2005). Besides, questionnaires are needed to investigate the users' preferences to the product samples using all the collected KWs (Kumar & Karla, 2013). The questionnaire uses the 5 levels of Likert scale to let users rate the product samples based on each KW (Kumar & Karla, 2013). The data collected from the

questionnaire are then calculated by using the mean (Kittidecha, Marasinghe, & Koichi, 2016). The mean values allow us to identify the preference attributes of product by the target groups.

The next step is to perform evaluation on validity of latest exploited model. The latest exploited model would be tested in the same situation, allowing target groups to evaluate them by answering questionnaires. The last stage is the model building. The final model is built based on the synthesis result. That is, after we gain synthesis results, a new model or design of the products will be produced based on the results obtained. For example, based on the result obtained from Kittidecha et al. (2016), the KWs “flexible”, “wrinkled” and “fine” has the highest mean among all the KWs. Therefore, Kittidecha et al. (2016) concluded and finalized their plastic foam products design in flexible, wrinkled and fine model.

2.8 Existing Recruitment Systems

We review 29 popular e-recruitment portals in Southeast Asia (see Appendix A). We will compare these job portals based on search function, skill level, job recommender and ranking component, and recruiting process.

2.8.1 Search Function

Search function is the search feature that enable users to quickly find their contents from the job portals. It works as search engine that helps visitors to query the contents they want in the job portals, for example job seeker can search the job by key in job title in search form which is provided in job portal. This is the most basic feature in job portals that can speed

up the searching process for the user when accessing the system. Searching criteria play important role in search function because they are tools allowing user to specific how the contents to be queried. All of these job portals provide a similar search criteria such as job titles, job positions, locations, specializations, salaries and company names. Figure 2.14 to 2.18 show the examples of quick search boxes on different job portals.

The image shows a search interface for BestJob Malaysia. It features a white search bar with a magnifying glass icon and the placeholder text "Write office or professional area". To the right of the search bar is a location dropdown menu showing "Kuala Lumpur" with a location pin icon. Further right is a red button with the text "Find jobs".

Figure 2.14: Quick search box on BestJob Malaysia.

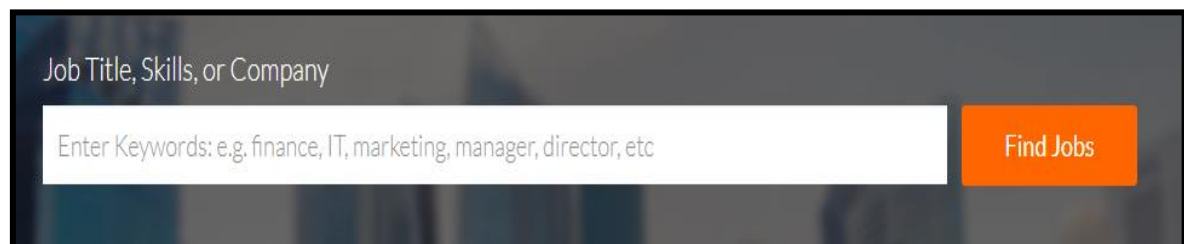
The image shows a search interface for Jobcentral. It features a dark grey header with the text "Job Title, Skills, or Company". Below this is a white search bar with the placeholder text "Enter Keywords: e.g. finance, IT, marketing, manager, director, etc". To the right of the search bar is an orange button with the text "Find Jobs".

Figure 2.15: Quick search Box on Jobcentral.

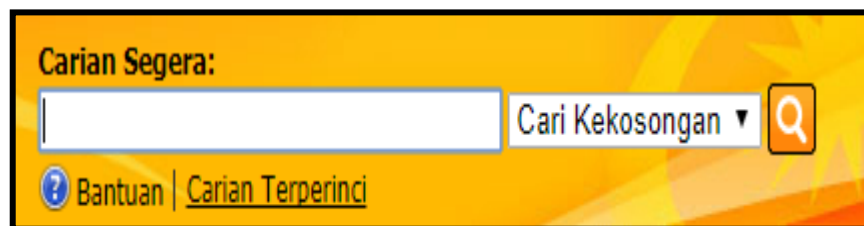
The image shows a search interface for JobMalaysia. It features a yellow background with the text "Carian Segera:" in bold. Below this is a white search bar with a magnifying glass icon. To the right of the search bar is a dropdown menu showing "Cari Kekosongan" with a downward arrow. Further right is a magnifying glass icon. Below the search bar is a blue question mark icon followed by the text "Bantuan" and a link "Carian Terperinci".

Figure 2.16: Quick search box on JobMalaysia.

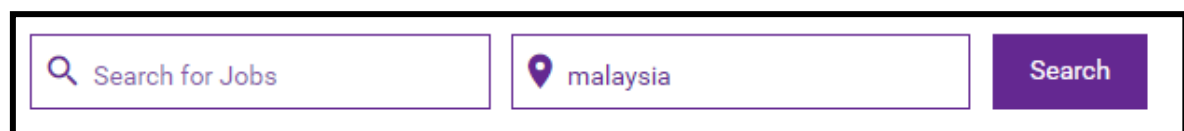
The image shows a search interface for Monster. It features a white search bar with a magnifying glass icon and the text "Search for Jobs". To the right of the search bar is a location dropdown menu showing "malaysia" with a location pin icon. Further right is a purple button with the text "Search".

Figure 2.17: Quick search box on Monster.

Q Job title or keyword Kuala Lumpur, 14, MY X Search All Jobs

Figure 2.18: Quick search Box on ZipRecruiter.

Based on quick box examples from Figure 2.14 to 2.18, the common search criteria for standard quick box feature in job portal include job title, company name and location. Apart from quick box feature, some of job portals provide advance search function, such as JobStreet, Naukri and Charkri. Figure 2.19 shows the examples of advanced search box on Naukri.

Advanced Search X

Keyskills Skills, Designation, Companies

Location Enter the cities you want to work in

Work Experience Select Years Select Month

Expected Salary Min in Lakhs

Industry Select the industry where you want to work
You can select at max 2 industries

Job Category Select your areas of expertise

Job Type All Jobs Company Jobs Consultant Jobs

Sort By Relevance Date

Search

Figure 2.19: Advanced search box on Naukri.

Advanced search feature in job portals provides more specific search criteria, such as job title, job position, company name, location, working experience, expected salary, education background, job sectors, job category and job types. Most of the job portals provide pre-defined option in search criteria, such as job sectors and job category sections, and display them in a dropdown form. Pre-defined option in search criteria can make job searching easier and convenient because it allows user to narrow the job searching scope. Figure 2.20 shows job sectors on Naukri, and Figure 2.21 shows search job category on Naukri.



Figure 2.20: Job sector section on Naukri.

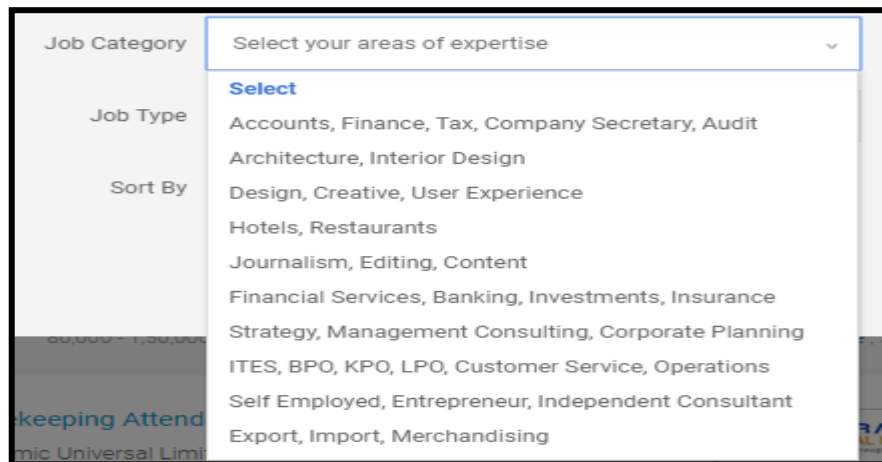


Figure 2.21: Job category section on Naukri.

2.8.2 Skill Levels

Skill level is one of the requirements to meet for hiring or get the job application in the job portals. All the job portals above are mainly designed for professional or skilled job which needs at least a diploma certificate to be eligible for job application. Most of the job portals are still for the recruitment unskilled jobs except for the Charkri, Jobhouse, JobSpot, KareerKo and Daijob which comprises only the skilled occupation post. Apart from that, there are two job portals which included the unskilled job search criterion- education qualification in the job portals, they are Jobcental and Maukerja. For these two job portals, they allow user to choose the education qualification from primary school level to master or

PHD level. Figure 2.22 shows the primary school level (UPSR) for education level on Maukerja.

The screenshot shows a search filter interface titled 'Tapis'. It includes three sections of filters: 'Gaji' (Salary) with five ranges, 'Minimum Pendidikan' (Minimum Education) with six levels, and 'Jenis Pekerjaan' (Job Type) with three categories. The 'UPSR (320)' option under 'Minimum Pendidikan' is highlighted with a dark background. At the bottom right are 'Padam' and 'Search' buttons.

Filter Category	Filter Option	Count
Gaji	0 - 1500	4910
	1500 - 3000	6428
	3000 - 5000	3798
	5000 - 10000	1820
	10000 - *	555
Minimum Pendidikan	Diploma	7175
	SPM	6451
	Any	1990
	Degree	1564
	UPSR	320
	Master/PHD	11
Jenis Pekerjaan	Full Time	13681
	Internship	3536
	Part Time	1718

Figure 2.22: Primary School Level (UPSR) for Education Level on Maukerja

2.8.3 Job Recommender and Ranking Component

Job recommender and ranking system is the intelligence system which automates the recommendation and ranking process of candidates in the job portals. Not all of the job portals above consists of this advanced intelligence features, for example Springasia, JobMalaysia, CareerJet, SPA, Glass Dour, Jobhouse, and Daijob. Next, there is only 5 out of 29 job portals implement the candidate ranking and commend system in the job portals, they are JobStreets, Monster, KareerKo, Recruit.net and ZipRecruiter. Therefore, most of the job portals do not emphasize on the candidate ranking and commend problem in job

portals. Figure 2.23 shows the recommendation job component on JobStreet, and Figure 2.24 shows the company’s ranking component on JobStreet.

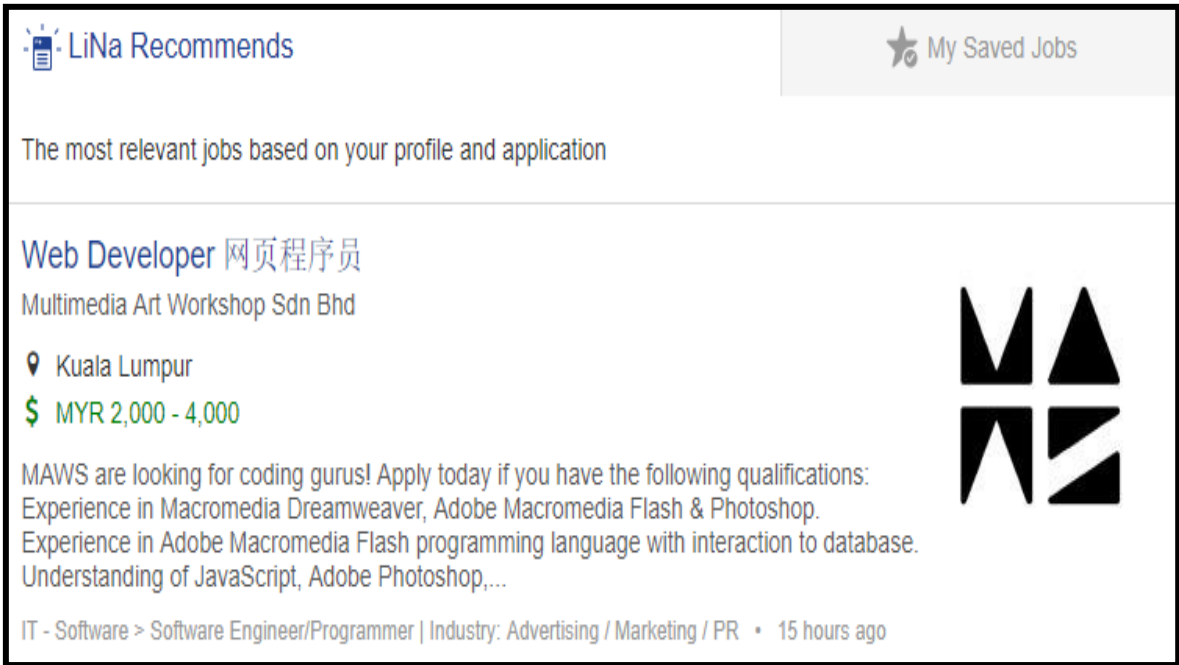


Figure 2.23: Job recommendation component on JobStreet.

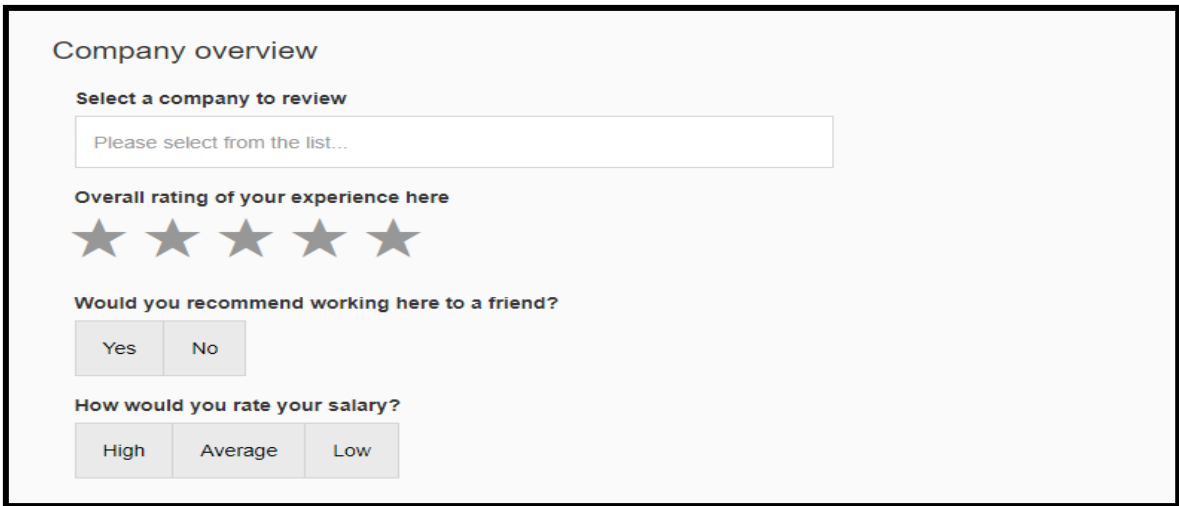


Figure 2.24: Company's rating component on JobStreet.

2.8.4 Recruitment Process

Recruitment process stands for the procedure in the job portals from job posts to candidate hired. All of the job portals above follow the standard e-recruitment process which from

getting job posts, filling in details, uploading resume, writing CVs and submit application. One of the job portals which look outstanding in the recruiting process is the BestJob Malaysia. In this job portal, it requires the user to answer the Labour Proficiency Test to allow the recruiter to understand more about the user in the aspect of responsibility on work. Figure 2.25 shows the Labour Proficiency Test on BestJob Malaysia. Table 2.8 shows the summary of existing job portals in Asia.



Figure 2.25: Labour proficiency test on BestJob Malaysia.

2.9 Conclusion

In summary, this chapter reviewed on the job recruitment process, job classification in Malaysia, Kansei Engineering Model, personality trait needed for job recruitment process, candidate filtering and ranking technique in job recruitment, and the strengths and weakness for each existing job portals are helping on this research which using FMCDM in candidate filtering for unskilled occupation.

Table 2.8: Summary of Existing Popular Job Portals in Asia

No.	Job Portals	Searching Criteria	Skill Level			Recommender & Rating System			Recruiting Process	
		Job Titles, Position, Location, Specialization, Salary, Company Name	Skilled Job	Semi-skilled Job	Unskilled Job	Recommender	Rating	Commend	Resume & CVs	Test
1	JobStreets	√	√	√	√	√	√	√	√	
2	SpringAsia	√	√	√					√	
3	Naukri	√	√	√	√	√			√	
4	JobMalaysia	√	√	√					√	
5	Looking4Job	√	√	√		√			√	
6	BestJob Malaysia	√	√	√		√			√	√
7	JobCentral	√	√	√	√	√			√	
8	Monster	√	√	√	√	√	√	√	√	
9	KareerKo	√	√			√	√	√	√	
10	JenJobs	√	√	√	√	√			√	
11	Indeed	√	√	√	√	√			√	
12	MauKerja	√	√	√	√	√			√	
13	Recruit	√	√	√	√	√	√	√	√	
14	MystarJob	√	√	√	√	√			√	
15	CareerJet	√	√	√	√				√	
16	SPA	√	√	√					√	
17	bdJobs	√	√	√		√			√	

Table 2.8 continued

No.	Job Portals	Searching Criteria	Skill Level			Recommender & Rating System			Recruiting Process	
		Job Titles, Position, Location, Specialization, Salary, Company Name	Skilled Job	Semi-skilled Job	Unskilled Job	Recommender	Rating	Commend	Resume & CVs	Test
18	GlassDoor	√	√	√	√				√	
19	Mjob	√	√	√	√	√			√	
20	JobCity	√	√	√	√	√			√	
21	Charkri	√	√			√			√	
22	JobHouse	√	√						√	
23	Kerjaya	√	√	√	√	√			√	
24	Startup Job	√	√	√	√	√			√	
25	Daijoob	√	√						√	
26	Jobspot	√	√			√			√	
27	ZipRecruiter	√	√	√	√	√	√	√	√	
28	JobsDB	√	√	√	√	√			√	
29	GigaJob	√	√	√	√	√			√	

CHAPTER 3

METHODOLOGY

3.0 Introduction

This chapter presents on the methodology use in this study for unskilled workers filtering and ranking by using FMCDM approach. For this chapter, it includes the framework of methodology. This framework of methodology explains the whole system development process.

3.1 Framework of Methodology



Figure 3.1: Framework of methodology in developing the proposed system.

Figure 3.1 clearly shows the whole system development process in developing the proposed system. The first step is Kansei Engineering Model, following step is assignment of importance to criteria. Next, construct the architecture of the system. After that, applying the F-TOPSIS which is one of the famous FMCDM approach in the system for unskilled candidate filtering and ranking. Lastly, the evaluation for the system takes place.

3.1.1 Kansei Engineering Model

KE model is the first stage in overall process of this system framework. KE can translate technology of human feeling toward the design of the product. Therefore, it is powerful model to get the human preferable design of the product. In this research, the main purpose

of applying KE model is to get the human resource managers or recruiters' preferable personality traits during the recruitment process. Once the preferable personality traits are collected, it can be considered as fuzzy variables which needed in the next stage- collecting of importance of fuzzy weight. There are 5 steps in this stages which included the selection of product domain, collection of personality trait and Kansei words (KWs), design questionnaire, data collection and analysis by using statistical method which is calculating the mean which is adopted from the solution from Kittidecha et al. (2016).

Step 1: Select the product domain. In this research, researchers view the job applicants as the product domain in the understanding of preferences of candidates or alternatives in recruitment for human resource manager or recruiters. This is because understanding of both preferable requirements is the main domain in this research.

Step 2: Collection of personality traits and Kansei words. 50 personality traits related to workspace and recruitment have been collected through dictionary search (Aarts, Chalker, & Weiner, 2014), from journal articles (Barrick & Mount, 1991), and interview with existing unskilled workers and employers. The Big Five Personality Traits model are also included as part of the KWs. Table 3.1 shows the list of personality traits in workspace and job recruitment.

Table 3.1: List of personality traits in workspace & job recruitment.

Adventure	Competitive	Efficient	Inexperienced	Neurotic
Ambitious	Confidence	Eloquent	Inquisitive	Open-minded
Approachable	Courteous	Energetic	Punctual	Opinionated
Articulate	Creative	Enthusiastic	Quiet	Organized
Autonomous	Curiosity	Flexible	Relaxed	Patient
Calm	Determined	Focused	Responsible	Perceptive
Charismatic	Devoted	Friendly	Technological	Persuasive
Cheerful	Diligent	Honest	Insightful	Procedural
Clever	Easy Going	Imaginative	Intuitive	Resourceful
Cooperative	Educated	Independent	Cost Salary	Talkative

Apart from that, two recruiters from Advantage Point Enterprise agency and Mondelez Malaysia Sales Sdn Bhd, two experts in human resources from University Malaysia Sarawak, and six human resource managers from unskilled job categories had interviewed by researchers. The unskilled job sectors includes construction, hotel, manufacturing, restaurant, sales and service. Fifty of personality traits which are unrelated to unskilled occupations are screened out by all of the experts during the interview sessions. From there, twenty personality traits are short-listed. KWs based on the remaining twenty personality traits were collected in Table 3.2.

Table 3.2: List of selected KWs.

KWs (-ve)	KWs (+ve)
Work bad with others	Work well with others
Develop negative work environment	Develop positive work environment
Get along bad in a team settings	Get along well in a team settings
Afraid to ask question	Not afraid to ask question
Do not eager to learn	Eager to learn

Table 3.2 continued

Do not always work hardest	Always work hardest
Do not adapt to new situation	Adapt to new situation
Very slow turnover time	Very quickly turnover time
Cannot work long and hard hours	Able to work long and hard hours
Cannot adapt self-priorities	Willing to adapt for matching work properties
Difficult to work with other colleagues	Easy to work with other colleagues
Cannot work by its own	Can work by its own
Inexperience	Experienced
Do not follow order or structure of company	Work best with structure
Bad time management skills	Great time management skills
Not trustworthy	Trustworthy
Over the maximum wages	Under the maximum wages
Cannot sense when there is problem	Can sense when there is problem
Easily ruffled	Not easily ruffled
Cannot finish task on time	Can finish task on time

Step 3: Design questionnaire. Questionnaire was designed to investigate human resource managers and recruiters' preferences to the 20 KWs in job recruitment process. This questionnaire consists of closed ended questions were constructed by using the 5 scores Likert scale: 1 is very disagree, 2 is disagree, 3 is neutral, 4 is agree, and 5 is very agree. Table 3.3 shows a sample item in the questionnaire.

Table 3.3: A sample of KE questionnaire item.

No.	Personality	Kansei Words (-ve)	VD	D	N	A	VA	Kansei Words (+ve)
			1	2	3	4	5	
1	Approachable	Work bad with others	1	2	3	4	5	Work well with others

Step 4: Data collection. 60 managers or recruiters have been interviewed by the author with purposive sampling method. The data collection process was conducted, starting from 25th of May, 2016 till 7th of August, 2016. The target groups fall into the 6 unskilled job sectors and there are 10 participants from each job sectors. During the interview, the researcher asked interviewees about the requirements and prominent of personality traits that they emphasize on unskilled job workers during the recruitment process. While pointing out their preferences on different personality traits, the researcher also asked interviewees about methods of recruitment of unskilled job worker in their organizations.

Step 5: Analysis. The collected data were analysed by using a statistical tool that calculate the mean of Kittidecha et al. (2016). The mean indicates the subsequent rating for each of the KWs. The subsequent rating is used to determine how the target group values different KWs that make up the perfect domain (Kumar & Karla, 2013). It is a technique for weighting different product concept (KWs) to identify which KW is preferred and favoured by the certain target group (unskilled job employers or recruiters). The formula to calculate the mean is shown in Equation (74).

$$\mu(y_j) = \frac{1}{n} \sum_{i=1}^n x_i, j = 1, 2, \dots, n \quad (74)$$

where $\mu(y_j)$ suppose to be rating to the y_j KWs; n is the total sample size; x_i is the i th employer assigns preference score to y_j KWs

3.1.2 Assignment of Importance of Criteria

Assignment of importance to criteria is the second stage in overall process of this system framework. In this stage, the 20 preferences of Kansei words obtained from the previous

stage are considered as the criteria for recruitment of unskilled worker. These criteria are presented as linguistic variables. Five human resources experts from Everrise Departmental Store Sdn Bhd (HQ) from Kuching, Sarawak were interviewed by the researcher with the purposive sample method. These data are collected for case study A. During the interview, importance of each criteria, according to the requirements and expectation for recruitment of unskilled workers had assigned by all the respondents. The questionnaire was constructed by using the 7 scores Likert scale: 1 is definitely very low, 2 is low, 3 is medium low, 4 is medium, 5 is medium high, 6 is high and 7 is very high. Table 3.4 shows a sample of item in the questionnaire.

Table 3.4: The sample of importance to criteria questionnaire.

No.	Personality	VL	L	ML	M	MH	H	VH
		1	2	3	4	5	6	7
1	Approachable	1	2	3	4	5	6	7

3.1.3 Construction of Architecture of the System

Architecture of the proposed system was constructed based on the integrated architecture for candidate filtering component which adapted by Laumer and Eckhardt (2009) in Figure 2.3. Some modifications are needed to be applied to fulfil the requirements and objectives in this research. Figure 3.3 shows the architecture of the proposed recruitment system. In Figure 3.3, we used different colours to indicate the five distinct components of the system. The accent orange colour indicates the employer whereas the green colour indicates the job seeker. Next, the colour of accent gold implies the F-TOPSIS subsystem which is the main component of this research, and the accent blue colour denotes the other subsystems in this proposed system. Lastly, the light blue colour manifests the database.

This database management subsystem is responsible for storing key data used by the system and managing the creating, reading, updating and deleting (CRUD) jobs for the incoming data from other subsystems, such as from the user management subsystem, F-TOPSIS subsystem and job post management subsystem. It also helps to specific the logical organization for a database, and accesses the information within the database. For instance, it provides the functions for managing information access, complying data incorruptness, administering data controller and restoring database. Figure 3.2 shows the entity relationship diagram of the proposed system.

Workflow management subsystem works as the whole infrastructure of the proposed system. It manages the whole system's workflow. It is because workflow management subsystem conforms all other subsystem to sustain the whole scope of recruiting processes. It is important in defining, controlling and coordinating different business logic behind the system. For example, after job seekers key in their job application data in job application form, workflow management system triggers the job post management subsystem to receive the data input from job seekers, and send it to the employer or company.

The user management subsystem is mainly focuses on the 2 types of users in the proposed system. They are job seekers and the employers or the recruiters. This subsystem is mainly used for user registration, user authentication and managing user profiles.

The job posts management subsystem is for handling the job advertisement in the proposed system. Employers or recruiters need to fill in a job title, description, and preference criteria for the job position before a job post is saved into database. This subsystem also allows

recruiters to view job applicants for a job they posted. For job seekers, they can view the all job offers through this subsystem. If they want to apply for a posted job, they need to fill in the application form and will be notified on their application status.

The F-TOPSIS subsystem is implementing the F-TOPSIS algorithm and calculation based on the preference criteria of employers for each job offers. It also responsible for suggesting the suitable jobs for unskilled job seekers. The results are send to filtering, ranking and recommender subsystem in order to notify the employers and job seekers. Employer can search and get the recommended candidate or job seeker through filtering, ranking and recommender subsystem whereas job seeker can search the suitable and preference job through the filtering, ranking and recommender subsystem.

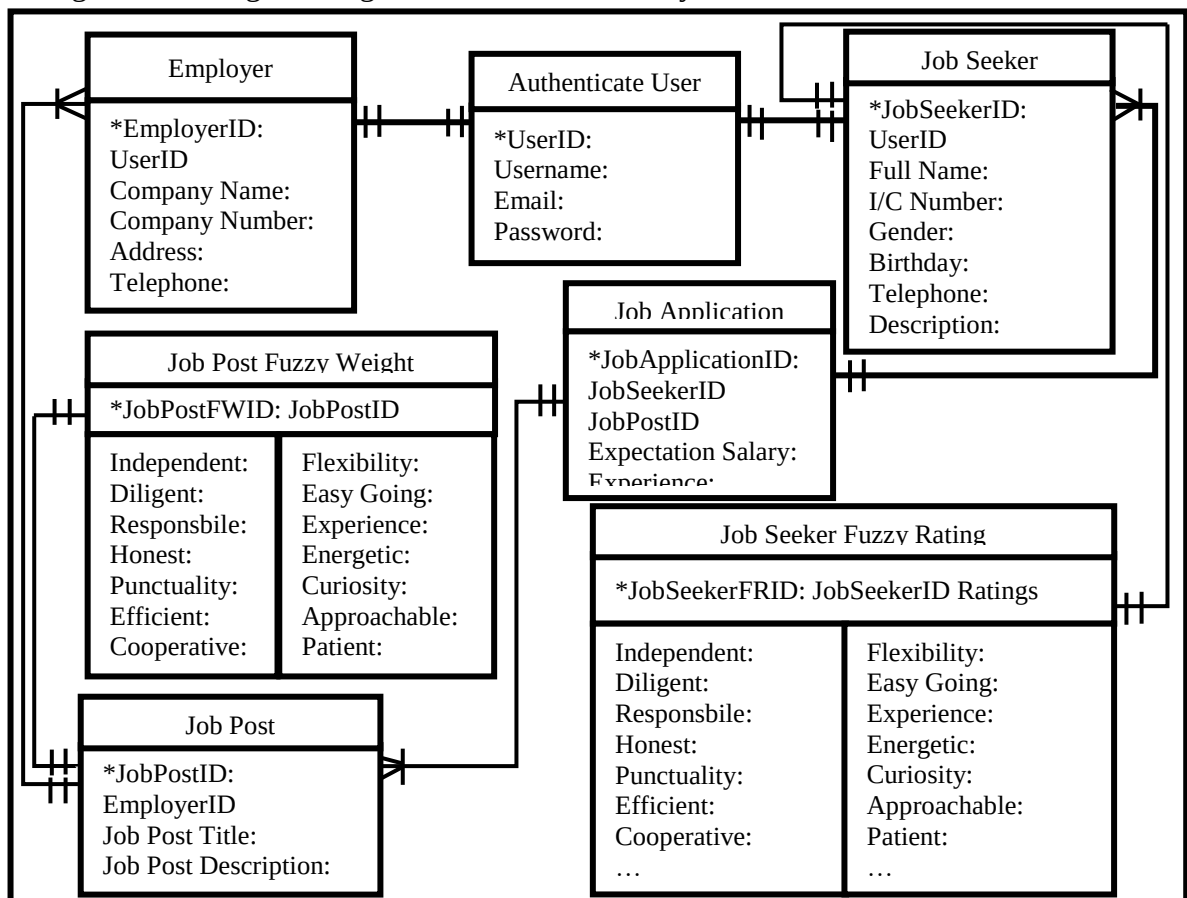


Figure 3.2: Entity relationship diagram of proposed system.

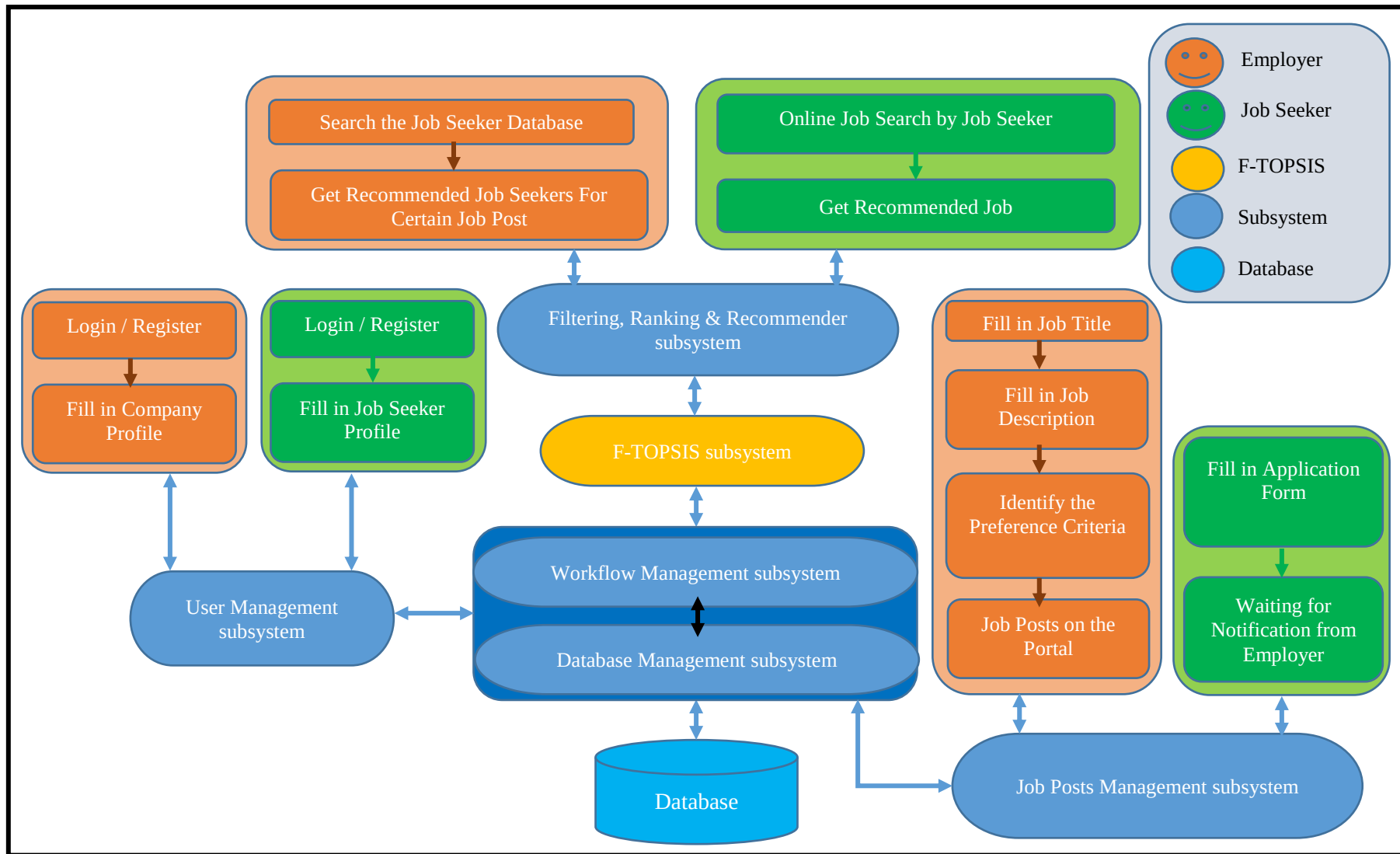


Figure 3.3: Architecture of the proposed system.

3.1.4 FMCDM Engine

FMCDM engine is the main component in our proposed system. We employed the F-TOPSIS (Hwang & Yoon, 2012) for candidate filtering and candidate recommendation in this study. This is because F-TOPSIS shows the outstanding performance in previous studies (Dursun & Karsak, 2010; Boran, Genç, & Akay, 2011; Kelemenis et al., 2011). As mentioned by Dursun & Karsak (2010), F-TOPSIS is good in personnel selection. They integrated fuzzy set theory with TOPSIS algorithm as the methodology to solve the personnel selection problem in hiring the Industrial Engineer. They had proved that the F-TOPSIS allows the recruiters or manager to deal with jumbled selection criteria (Dursun & Karsak, 2010). The eight criteria they used for hiring the Industrial Engineer included talent, knowledge, confidence, emotional control, leadership, communication skill, personality and experience (Dursun & Karsak, 2010).

Boran et al. (2011) also stated that F-TOPSIS is a suitable solution to solve the multiple criteria decision-making problems like personnel selections. It is because it consists of indistinct consciousness of recruiters or managers' opinion. Boran et al. (2011) used F-TOPSIS to select the best sales manager in a manufacturing company. Additionally, Kelemenis et al. (2011) showed that F-TOPSIS enables to deal with the recruiters or managers' recruiting problem, especially dealing with imprecise information and ambiguous opinion. Their proposed system able to support the decision-making in IT professional selection problem. Based on the result by Kelemenis et al. (2011), F-TOPSIS able to eliminate biased and unfair judgements from different recruiters in a recruiter team.

F-TOPSIS also requires less computations compare with other techniques. Furthermore, it

is more flexible than other techniques as it does not need to organize the problem into hierarchical structure like F-AHP and F-ANP. In the following we show the steps of F-TOPSIS algorithm.

Step 1: Form decision-making groups. After N number of decision-makers had formed from the target group, such as the human resource experts or recruiters from unskilled job sectors. The fuzzy rating of each decision-maker $D_n = (n = 1, 2, \dots, N)$ can be defined as triangular fuzzy number $\tilde{R}_n = (n = 1, 2, \dots, N)$ with membership function $\mu_{\tilde{R}_n}(x)$.

Step 2: Identify evaluation criteria. Evaluation criteria need to be identified by the human resource experts or recruiters in different unskilled occupation sectors. This is done from the selected Kansei words in the first stage of the framework of methodology – Kansei Engineering Model.

Step 3: The appropriate linguistic variable is determined. The same linguistic variables are derived from Wang and Lee (2009). The purpose for these linguistic variables is to evaluate the job position criteria and job candidates or job applicants.

In this study, the fuzzy weight matrix for each criterion is evaluated and assigned by the decision-making group based on the linguistic variables (Wang & Lee, 2009) as illustrated in Figure 3.4 and Table 3.5. These terms are defined in the structure of triangular fuzzy number. The importance of criteria is ranging from “Very Low (VL)” to “Very High (VL)”.

Table 3.5: Fuzzy linguistic terms and respective fuzzy numbers for each criterion weight.

Linguistic Terms	Fuzzy Number
Very Low (VL)	(0,0,0.2)
Low (L)	(0.05,0.2,0.35)
Medium Low (ML)	(0.2,0.35,0.5)
Medium (M)	(0.35,0.5,0.65)
Medium High (MH)	(0.5,0.65,0.8)
High (H)	(0.65,0.8,0.95)
Very High (VH)	(0.8,1.0,1.0)

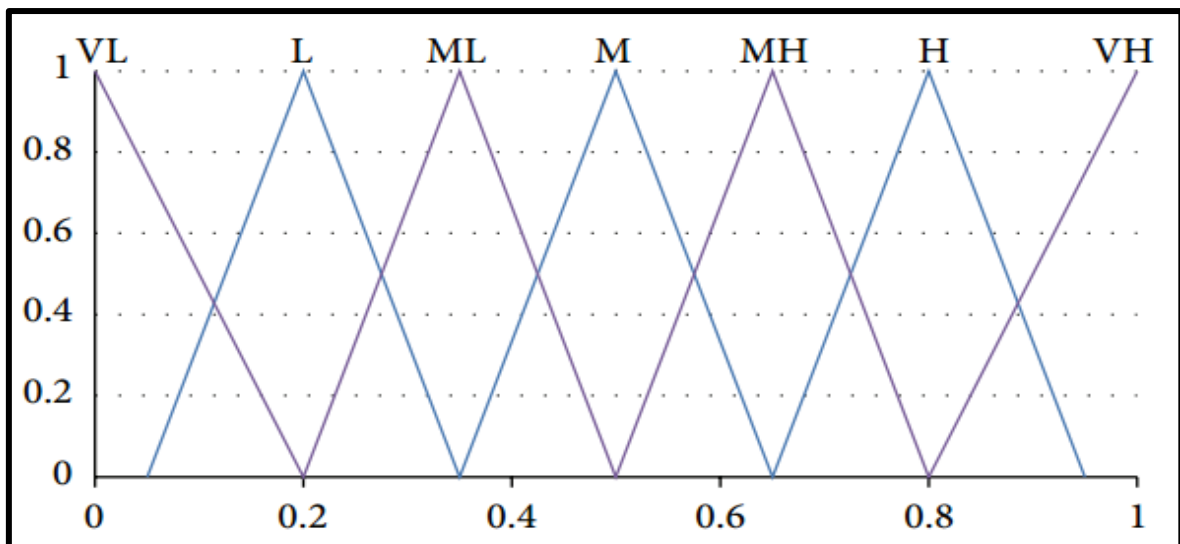


Figure 3.4: The fuzzy linguistic variables for each criterion weight.

Step 4: Both subjective weighting method and entropy-based objective weighting method is applied. Subjective weighting method is to determine the decision groups' weights for each criterion (Wang & Lee, 2009). The formula of subjective weighting described in Equation (67) (Md Saad et al., 2014).

According to Wang and Lee (2009), entropy-based objective weighting method extends Shannon's concept which applies entropy measure to calculate the objective weight. The entropy weight mainly uses to determine the differences candidates approaches to one another in terms of each criterion. The larger the entropy value, the smaller the entropy weight. Firstly, the interval valued fuzzy number needs to be transformed into crisp number in Equation (68) (Chaghooshi et al., 2012) with the α -cut of triangular fuzzy number in Equation (65) (Md Saad et al., 2014) before applied the Shannon's entropy algorithm. Next, fuzzy weight matrix can be normalized in order to get the projection value for each criterion, P_{ij} , in equation (66) (Wang & Lee, 2009). After that, entropy values can be calculated in Equation (69) (Wang & Lee, 2009) after project value for each criterion is calculated.

The degree of divergence d_i of the inherent data of each criterion $C_j (j = 1, 2, \dots, n)$ may be calculated in Equation (70) (Wang & Lee, 2009). The degree of divergence shows the intrinsic contrast intensity divergence c_i . The higher the d_i , the more important for the criterion, c_i . The objective weight can be calculated in Equation (71) (Wang & Lee, 2009).

Step 5: The weight of criteria is aggregated. If all the fuzzy ratings are defined as triangular fuzzy number in Step 1, then the aggregated fuzzy ratings can be described as $\tilde{R}_n = (a, b, c)$, $n=1,2,3,\dots,N$, where N is the total number of criteria. Here is the formula to aggregate the weight of criteria which display in Equation (75) (Wang & Lee, 2009).

$$\tilde{X}_{ij} = \frac{1}{n} \left(\sum_{e=1}^n \tilde{X}_{ij} \right), i = 1, 2, 3, \dots, m \quad (75)$$

where m is the total number of decision makers, and $\tilde{X}_{ij}$ is the i decision maker assign weight to m criterion .

Step 6: Construct fuzzy decision matrix. The sample of fuzzy decision matrix is shown in Equation (76) (Ertuğrul & Karakaşoğlu, 2008).

$$\tilde{D} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \dots & \tilde{x}_{1D} \\ \tilde{x}_{21} & \tilde{x}_{22} & \dots & \tilde{x}_{2D} \\ & & \dots & \\ & & & \dots \\ & & & \dots \\ \tilde{x}_{A1} & \tilde{x}_{A2} & \dots & \tilde{x}_{AD} \end{bmatrix} \quad \tilde{W} = [\tilde{w}_1, \tilde{w}_2, \tilde{w}_3, \dots, \tilde{w}_D] \quad (76)$$

where $\tilde{x}_{cd} = (a_{cd}, b_{cd}, c_{cd})$ and $(\tilde{w}_d) = (w_{d1}, w_{d2}, w_{d3})$; $c = 1, 2, 3, \dots, A, d = 1, 2, 3, \dots, D$ is considered as the positive triangular fuzzy number.

In this study, the fuzzy decision matrix for each candidate is evaluated and assigned by the decision-making group based on the linguistic variables which is adopted from Wang and Lee (2009) as illustrated in Figure 3.5 and Table 3.6. These terms are like step 5. They are defined in the structure of the triangular fuzzy numbers. The performance evaluation is ranging from “Very Poor (VP)” to “Very Good (VG)”.

Table 3.6: Fuzzy linguistic terms and respective fuzzy numbers for each candidate.

Linguistic Terms	Fuzzy Number
Very Poor (VP)	(0,0,0.2)
Poor (P)	(0.05,0.2,0.35)
Medium Poor (MP)	(0.2,0.35,0.5)
Fair (F)	(0.35,0.5,0.65)
Medium Good (MG)	(0.5,0.65,0.8)
Good (G)	(0.65,0.8,0.95)
Very Good (VG)	(0.8,1.0,1.0)

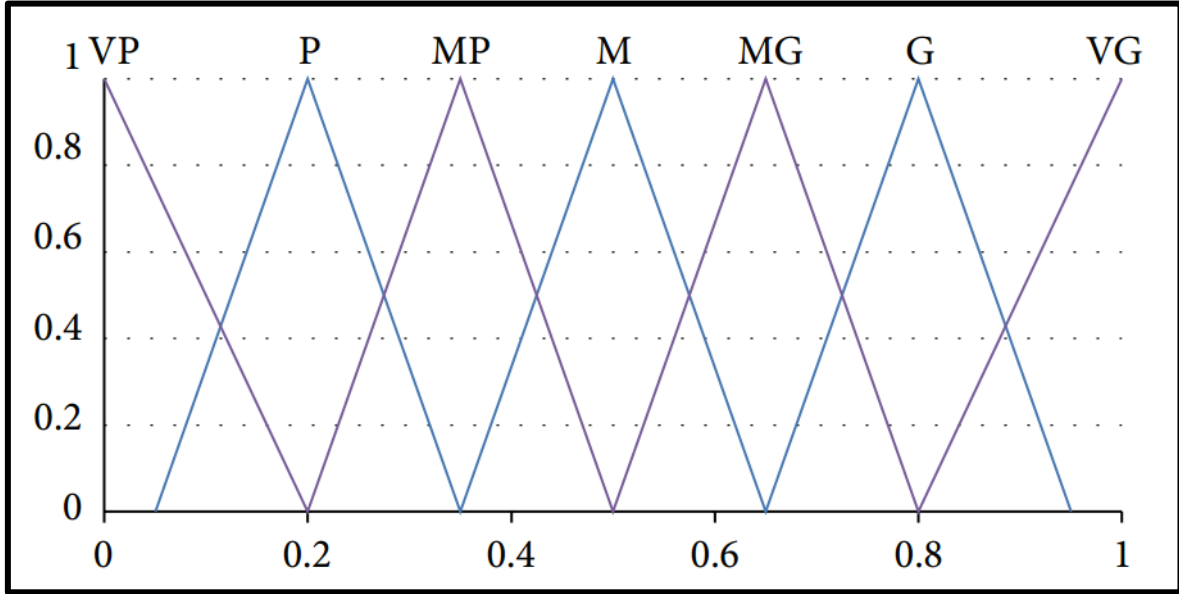


Figure 3.5: The fuzzy linguistic variables for each candidate.

Step 7: Normalization. The linear scale transformation was used transform criteria scales into a comparable scale which shown in Equation (25) (Ertuğrul & Karakaşoğlu, 2008).

Step 8: Weighted normalization fuzzy decision matrix is constructed. The weighted normalized decision matrix is computed by multiplying the importance weight of evaluation criteria and values in normalized fuzzy decision matrix. Thus, the final fuzzy normalized fuzzy would be shown as $\tilde{V}$ in Equation (27) (Ertuğrul & Karakaşoğlu, 2008).

Step 9: FPIS and FNIS is defined. FPIS is defined as Equation (28), and FNIS is defined as Equation (29) (Ertuğrul & Karakaşoğlu, 2008).

Step 10: The distance between each criteria and FPIS, and the distance between each criteria FNIS are calculated. Based on Bojadziev and Bojadziev (1995), the distance between two triangular fuzzy number $A_1 = (a_1, b_1, c_1)$ and $A_2 = (a_2, b_2, c_2)$ can be

calculated in Equation (32) (Wang & Lee, 2009). Next, the both formulas to calculate the FPIS and FNIS distance are shown in equation (30) and (31) respectively (Ertuğrul & Karakaşoğlu, 2008).

Step 11: The closeness of coefficient is defined. The closeness of coefficient stands for the distances to FPIS (A^*) and FNIS (A^-) simultaneously. The closeness of coefficient for each candidates is calculated in Equation (33) (Ertuğrul & Karakaşoğlu, 2008).

Step 12: The ranking of candidates are defined. Based on Ertuğrul and Karakaşoğlu (2008) and the Equation (33), the best candidate A_i would be closer to FPIS and farther from FNIS if and only if CC_i approaches to 1.

3.1.5 Evaluation

A numerical example on the unskilled worker selection in a sales and marketing unskilled job sector is provided to validate and evaluate the proposed system and algorithm in the recruitment of unskilled worker. This numerical example is called as Case Study A – Company A. Twenty real candidates' data were provided by Company A. Meanwhile, the five sets of importance of criteria towards the recruitment of unskilled workers were collected from five human resources recruiters from Company A respectively. On the other hand, decision matrix for candidate's evaluation on each criterion was assigned by the same linguistic variable Wang and Lee (2009) as illustrated in Figure 3.5 and Table 3.6.

The first evaluation method is by using the hamming distance Md Saad et al. (2014). As mentioned, hamming distance technique is another existing and well-known MCDM which

calculates the distance in order to get the best candidate. Therefore, it can be used to validate the proposed method by using F-TOPSIS (Md Saad et al., 2014). The steps in hamming distance method are listed as following:

Step 1: Construct the ideal candidate matrix. Ideal candidate matrix is constructed based on linguistic variables which adopted from Wang and Lee (2009) as illustrated in Figure 3.5 and Table 3.6. During the interview, five experts from Company A need to come to an agreement in normalizing their own ideal alternatives' values into one final best value for each criterion which is accepted by all five experts (Md Saad et al., 2014).

Step 2: Construct the normal decision matrix for all twenty candidates. Decision matrix for all twenty candidates was constructed based on the linguistic variables which assigned by decision groups. The linguistic variables are adopted from Wang and Lee (2009) as illustrated in Figure 3.5 and Table 3.6.

Step 3: Construct the fuzzy weight matrix for all criteria. Importance to criteria are assigned by 5 experts which is done in previous stage 2 of framework of methodology-assignment of importance of criteria.

Step 4: Construct an interval-valued fuzzy number. The interval-valued fuzzy number was constructed by α -cut of triangular fuzzy number which is illustrated in Equation (65). α numbers are adopted from Md Saad, Ahmad, Abu, and Jusoh (2014), where α numbers are 0 and 0.5 respectively.

Step 5: Normalization of Fuzzy Weight. Projection value P_{ij} is obtained from the Equation (66). A projection matrix is constructed based on each projection value.

Step 6: Calculate both subjective and objective weight. This is done in previous stage 4 which belongs to FMCDM in candidate filtering.

Step 7: Calculate distance values between the best candidates with each candidate. Each distance between the best candidate with each candidate is calculated based on the subjective weight which is illustrated in Equation (72), and objective weight which is presented in Equation (73) (Md Saad et al., 2014).

Step 8: Rank the candidate based on the distance obtained from step 7. The candidates are ranked in ascending order based on the distance results from step 7. Therefore, the candidate with the shortest distance is the best candidate who is going to be recommended for the job position.

The second evaluation method is by comparing the ranking result from five experts of Company A with the ranking result from the proposed system. From the comparison of both result, it can clearly compare the similarity result for both human experts and the proposed system.

Apart from that, Cohen's Kappa coefficient technique is applied to verify the reliability of inter-rater agreement between proposed solution and hamming distance method, and reliability of inter-rater agreement between proposed solution and five human experts from

DM groups. Cohen's Kappa coefficient technique is proposed by Cohen in 1960 (Fleiss, Levin, & Paik, 2013). Cohen's Kappa coefficient technique is widely used in many areas, such as Biological (Fattahi, Othman, & Othman, 2015) and emotional categorical (Juremi, Zulkifley, Hussain, & Zaki, 2017).

The steps in Cohen's Kappa are listed as following:

Step 1: Construct contingency table. Contingency table is applied to access the agreement of k number of alternative between raters (Fleiss et al., 2013). Table 3.7 shows the example of contingency table for Cohen's Kappa Coefficient Technique (Fattahi et al., 2015).

Table 3.7: Two raters proportion with k alternatives.

Rater 1	Rater 2				Total
	1	2	...	k	
1	P_{11}	P_{12}	...	P_{1k}	P_{1+}
2	P_{21}	P_{22}	...	P_{2k}	P_{2+}
...	...	...	...	...	...
k	P_{k1}	P_{k2}	...	P_{kk}	P_{k+}
Total	P_{+1}	P_{+2}	...	P_{+k}	1

Step 2: Calculate relative observed agreement among raters and hypothetical probability of chance agreement. Relative observed agreement among raters, P_0 is calculated based on Equation (77) (Fleiss et al., 2013), whereas hypothetical probability of chance agreement, P_e is calculated based on Equation (78) (Fleiss et al., 2013).

$$P_0 = \sum_{i=1}^k P_{ii} \quad (77)$$

$$P_e = \sum_{i=1}^k P_{i+} P_{+i} \quad (78)$$

where k is the total number of alternatives.

Step 3: Calculate Cohen's Kappa. Cohen's Kappa, K is calculated based on Equation (79) (Fleiss et al., 2013).

$$K = \frac{P_0 - P_e}{1 - P_e} \quad (79)$$

Step 4: Evaluate Cohen's Kappa. Based on degree of agreement based on Cohen's Kappa Coefficient, as illustrated in Table 3.8, the inter-rater reliability among two raters is satisfying if and only if the obtained Cohen's Kappa, K is greater than 0.7 (Fleiss et al., 2013).

Table 3.8: Degree of agreement of Cohen's Kappa Coefficient (Fleiss et al., 2013).

Cohen's Kappa, K	Degree of Agreement
$0.8 < K \leq 1.0$	Excellent
$0.6 < K \leq 0.8$	Good
$0.4 < K \leq 0.6$	Fair
$K \leq 0.4$	Weak

3.2 Conclusion

In summary, creating a FMCDM in job recruitment system requires five stages which are Kansei engineering model, assignment of importance to criteria, architecture of the system, FMCDM engine in candidate filtering and job recommendation, and evaluation by hamming distance method and expert to compare the results.

CHAPTER 4

RESULTS AND DISCUSSION

4.0 Introduction

Our results are presented into three sections. The first section reports the prominent of Kansei words (KWs) during the recruitment of unskilled workers. The second section summaries the results of preference of Kansei words, and the last section illustrates the results of evaluation of the proposed system which includes the fuzzy decision matrix for real candidates of Company A, and the fuzzy weight matrix which is provided by 5 human resource experts, meanwhile discussing about the result of evaluation of the proposed system.

4.1 Result of Prominent of Kansei Words

Data collected from sixty employers in six different unskilled industries have been listed in Table 4.2. The data collection process was conducted, from 25th of May till 7th of August, 2016. The areas included Kota Samarahan, Jalan Petanak, Batu Kawah, Kuching, Sibul, Pasir Gudang, Johor Bahru and Petaling Jaya, Kuala Lumpur. These areas are selected based on the approval of person-in-charge in each outlet. The six different sectors of unskilled industries included construction, hotel, manufacturing, restaurant, sales and marketing, and service. As listed in Table 3.1, fifty personality traits in workspace and recruitment, were collected by the dictionary search (Aarts et al., 2014), the journal articles (Barrick & Mount, 1991), and the interviews with existing unskilled workers and employers. The big five personality traits are also included as a part of the KWs.

We had interviewed six human resource experts from unskilled job categories in order to screen out the personality traits unrelated to unskilled occupations. There are two recruiters from Advantage Point Enterprise agency, two recruiters from Mondelez Malaysia Sales Sdn Bhd, and two experts from Universiti Malaysia Sarawak (UNIMAS). One expert from UNIMAS has strong working experience in human resource area, who worked as Senior Human Resource (HR) Executive with job responsibilities to cover the administration of the full spectrum of HR functions, especially recruitment and selection. Next, another expert from UNIMAS had the Ph. D in Guidance and Counseling Programme who had the strong knowledge in Big Five Personality Traits which related to job recruitment. As a result, twenty personality traits which are related to unskilled occupations are shortlisted as illustrated in Table 4.1. Table 4.2 shows the preference score of each employer from six different unskilled industries for each KW.

Table 4.1: Personality traits for unskilled occupations.

No	Personality Traits for Unskilled Occupations
1	Responsible
2	Honest
3	Cooperative
4	Independent
5	Diligent
6	Easy going
7	Experience
8	Friendly
9	Cost
10	Efficient
11	Punctuality
12	Confidence
13	Approachable
14	Flexibility
15	Cheerful
16	Energetic
17	Procedural
18	Curiosity
19	Patient
20	Intuitive

Table 4.2: Frequencies of twenty KWs collected from sixty employers in six different unskilled job sectors

Kansei Words	Industries																													
	Construction					Hotel					Manufacturing					Restaurant					Sales					Service				
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
Approachable	0	0	5	3	2	0	0	1	4	5	0	2	0	3	5	0	0	2	6	5	0	0	4	4	2	0	0	6	1	3
Cheerful	0	2	2	3	3	0	0	3	5	2	0	1	1	6	2	0	0	1	3	6	0	2	1	5	2	0	0	5	2	3
Cooperative	0	0	2	5	3	0	0	2	5	3	0	0	3	4	3	0	0	0	3	7	0	1	2	1	6	0	0	3	3	4
Confidence	0	1	3	1	5	0	0	4	3	5	1	1	1	4	3	0	0	2	6	2	0	0	3	2	5	0	0	4	3	5
Curiosity	0	1	2	2	5	0	0	4	4	2	0	0	2	5	3	0	2	2	3	3	0	2	0	5	3	0	0	6	2	5
Diligent	0	1	1	4	4	0	0	2	5	3	1	0	1	4	4	0	0	2	4	4	0	0	0	5	5	0	0	2	5	3
Easy going	0	0	1	5	4	0	1	1	4	4	0	1	1	6	2	0	1	0	4	5	0	1	1	5	3	0	1	2	4	3
Efficient	0	0	2	6	2	0	1	0	6	3	1	0	4	1	4	0	0	2	4	4	0	0	3	1	6	0	0	5	3	2
Energetic	0	0	2	6	2	0	0	4	4	2	1	0	3	1	5	0	0	2	3	5	0	0	3	4	3	0	0	4	4	2
Flexibility	0	1	0	8	1	0	0	4	5	1	1	1	0	3	5	0	0	2	3	5	0	0	3	4	3	0	0	4	4	2
Friendly	0	2	1	4	3	0	0	1	3	6	0	1	0	7	2	0	0	1	5	4	0	2	2	3	2	0	0	3	3	4
Independent	0	0	2	2	6	0	0	4	4	2	1	0	2	3	4	0	0	4	3	6	0	0	2	1	7	0	0	3	4	3
Experience	2	1	3	2	2	0	3	4	2	1	1	0	2	3	4	1	1	1	5	1	0	0	4	2	4	0	1	3	5	1
Procedural	1	0	4	2	3	0	0	3	4	4	0	0	3	5	2	0	0	0	8	2	0	1	2	1	6	0	2	3	4	1
Punctuality	0	1	2	4	3	0	0	1	5	4	1	1	2	3	3	0	0	1	4	5	0	1	1	2	6	0	1	4	4	1
Honest	0	1	2	3	4	0	1	0	3	6	1	0	0	5	4	0	0	0	4	6	0	1	0	4	5	0	1	1	2	6
Cost	0	0	1	2	7	0	0	3	5	2	1	0	1	8	0	0	0	2	5	3	0	1	2	2	5	0	1	2	4	3
Intuitive	1	1	1	5	2	0	1	3	4	2	0	1	2	5	2	0	1	3	5	1	0	1	1	4	4	0	0	3	5	2
Patient	0	1	1	6	2	0	0	4	4	2	0	1	2	6	1	0	0	2	7	1	1	0	2	4	3	0	0	4	5	1
Responsible	0	1	1	4	4	0	0	1	3	6	0	1	0	5	4	0	0	0	6	4	0	1	1	2	6	0	0	2	2	5

Note: “Approachable”, there are five experts giving a score of three, three experts giving a score of four, and two experts giving a score of five.

The ratings of each KW from sixty employers for all unskilled industries have been summarised in Table 4.3. The ratings of each KW are calculated based on Equation (74). Additionally, Figure 4.1 shows the ratings for twenty KWs for all six industries. It is apparent that the most prominent KW for all industries is “responsible” whereas the least preferred KW is “experience”.

Table 4.3: Ratings of twenty KWs for all industries.

Kansei Words	Preference Score	Ratings (%)
Responsible	259	4.32
Honest	257	4.28
Cooperative	252	4.20
Independent	251	4.18
Diligent	250	4.17
Easy going	245	4.08
Friendly	244	4.06
Cost	242	4.03
Efficient	240	4.00
Punctuality	240	4.00
Confidence	237	3.95
Approachable	237	3.95
Flexibility	237	3.95
Cheerful	235	3.92
Energetic	235	3.92
Procedural	233	3.88
Curiosity	232	3.87
Patient	228	3.80
Intuitive	227	3.78
Experience	213	3.55

Note: Ratings of KW=preference score of KW/N, N=60.

As illustrated in Table 4.3, twenty KWs are arranged in a descending order based on the ratings of preference scores of KWs. The highest rating of KWs for all industries involved in this study is “responsible”, whose preference score is 259. Also, it is 4.32 percent of ratings from a total of sixty target respondents. Based on Equation (74), the ratings of

“responsible” obtained is demonstrated as $259/60 = 4.32$, where $n = 60$. The second highest of KW is “honest” with 259 preference scores (4.28 percent of ratings). This is then followed by “cooperative”, whose preference score is 252 (4.20 percent of ratings). Also, Table 4.3 exhibits that the least preferred KW for all industries is “experience”, which has only 213 preference scores, and is only 3.55 percent of ratings.

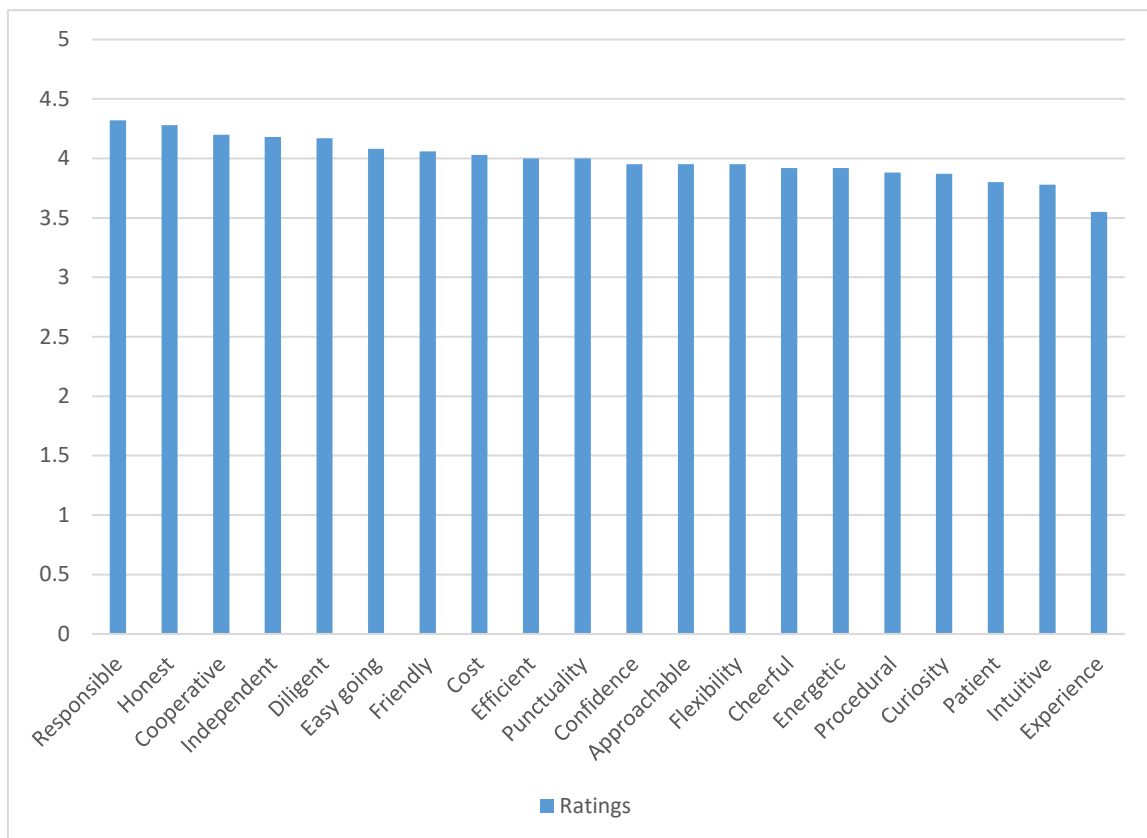


Figure 4.1: Ratings of twenty KWs for all industries.

The ratings of each KW based on different industries are calculated and presented from Table 4.4 to 4.9. The ratings for Table 4.4 to 4.9 are calculated by Equation (74). The twenty KWs are arranged in a descending order based on the ratings of preference scores. It is seen that different job sectors have different preferences on KWs.

Table 4.4: Ratings of twenty KWs for construction sector.

Kansei Words	Preference Score	Ratings (%)
Cost	46	4.60
Independent	44	4.40
Easy Going	43	4.30
Cooperative	41	4.10
Diligent	41	4.10
Curiosity	41	4.10
Responsible	41	4.10
Efficient	40	4.00
Energetic	40	4.00
Confidence	40	4.00
Honest	40	4.00
Flexibility	39	3.90
Punctuality	39	3.90
Patient	39	3.90
Friendly	39	3.90
Approachable	37	3.70
Cheerful	37	3.70
Procedural	36	3.60
Intuitive	36	3.60
Experience	31	3.10

Note: Ratings of KW=preference score of KW/N, N=10.

As Table 4.4 indicates, it is apparent that the highest rating of KW for construction is “cost”, whose preference score is 46 with 4.62 percent of ratings from a total of ten target respondents. Based on Equation (74), the ratings of “cost” obtained is demonstrated as $46/10 = 4.60$, where $n = 10$. This is followed by the “independent” with 44 preference scores (4.48 percent of ratings). The third preferred KW for construction is “easy going”, whose preference score is 43, and it is also 4.30 percent of ratings. Also, Table 4.4 illustrates the least relevant KW for construction is “experience”, which has only 31 preference scores (3.10 percent of ratings) among ten experts in construction.

Table 4.5: Ratings of twenty KWs for hotel.

Kansei Words	Preference Score	Ratings (%)
Responsible	45	4.50
Friendly	45	4.50
Approachable	44	4.40
Honest	44	4.40
Punctuality	43	4.30
Efficient	41	4.10
Easy going	41	4.10
Diligent	41	4.10
Cooperative	41	4.10
Procedural	40	4.00
Cheerful	39	3.90
Confidence	39	3.90
Cost	39	3.90
Patient	38	3.80
Independent	38	3.80
Energetic	38	3.80
Curiosity	38	3.80
Flexibility	37	3.70
Intuitive	37	3.70
Experience	31	3.10

Note: Ratings of KW=preference score of KW/N, N=10.

Table 4.5 shows that the highest rating of KWs for hotel is both “responsible” and “friendly”, having the same 45 preference scores (4.50 percent of ratings) from ten target respondents. Based on Equation (74), the ratings of “responsible” and “friendly” obtained are demonstrated as $45/10 = 4.50$, where $n = 10$. These are followed by the “approachable” and “honest” whose preference scores are 44 (4.40 percent of ratings). The third highest rating of KW for hotel is “punctuality”, with 43 preference scores at 4.30 percent of rating. Table 4.5 also reveals that the least favoured KW for hotel is “experience” which its preference score is 31 with 3.10 percent of ratings.

Table 4.6: Ratings of twenty KWs for manufacturing sector.

Kansei Words	Preference Score	Ratings (%)
Responsible	42	4.20
Approachable	41	4.10
Curiosity	41	4.10
Honest	41	4.10
Cooperative	40	4.00
Diligent	40	4.00
Flexibility	40	4.00
Friendly	40	4.00
Procedural	39	3.90
Experience	39	3.90
Independent	39	3.90
Energetic	39	3.90
Easy going	39	3.90
Cheerful	39	3.90
Intuitive	38	3.80
Patient	37	3.70
Efficient	37	3.70
Confidence	37	3.70
Cost	36	3.60
Punctuality	36	3.60

Note: Ratings of KW=preference score of KW/N, N=10.

As Table 4.6 reports, it is clear that the most preferred KW for manufacturing is “responsible”, whose preference score is 42 with 4.20 percent of ratings. Based on Equation (74), the rating of “responsible” obtained is demonstrated as $42/10 = 4.20$, where $n = 10$. This is followed by “approachable”, “curiosity” and “honest”, with same 41 preference scores (4.10 percent of ratings). The third highest rating of KWs for manufacturing are “cooperative”, “diligent”, “flexibility” and “friendly”. All of them have the same 40 preference scores (4.00 percent of ratings). Additionally, Table 4.6 also exposes that “cost” and “punctuality” are the least preferred KWs for manufacturing. They have the same least 36 preference scores (3.60 percent of ratings).

Table 4.7: Ratings of twenty KWs for restaurant.

Kansei Words	Preference Score	Ratings (%)
Cooperative	47	4.70
Honest	46	4.60
Independent	45	4.50
Cheerful	45	4.50
Responsible	44	4.40
Punctuality	44	4.40
Easy going	43	4.30
Flexibility	43	4.30
Friendly	43	4.30
Procedural	42	4.20
Energetic	42	4.20
Efficient	42	4.20
Diligent	42	4.20
Cost	41	4.10
Confidence	40	4.00
Approachable	40	4.00
Patient	39	3.90
Curiosity	37	3.70
Intuitive	36	3.60
Experience	36	3.60

Note: Ratings of KW=preference score of KW/N, N=10.

Table 4.7 demonstrates the ratings of twenty KWs for restaurant. It clearly shows that the highest rating of KW is “cooperative”, which it has preference scores of 47, and is 4.70 percent of ratings. Based on Equation (74), the rating of “cooperative” obtained is demonstrated as $47/10 = 4.70$, where $n = 10$. This is followed by “honest”, whose preference score is 46 (4.60 percent of ratings). The third highest rating of KWs are “independent” and “cheerful”, with same 45 preference scores (4.50 percent of ratings). Next, Table 4.7 also shows that the least favoured KWs are “intuitive” and “experience” whose preference scores are 36 (3.60 percent of ratings).

Table 4.8: Ratings of twenty KWs for sales and marketing.

Kansei Words	Preference Score	Ratings (%)
Independent	47	4.70
Diligent	46	4.60
Responsible	45	4.50
Honest	45	4.50
Punctuality	43	4.30
Efficient	43	4.30
Cooperative	42	4.20
Confidence	42	4.20
Procedural	42	4.20
Intuitive	41	4.10
Cost	41	4.10
Flexibility	40	4.00
Easy going	40	4.00
Experience	40	4.00
Energetic	39	3.90
Curiosity	39	3.90
Approachable	38	3.80
Patient	38	3.80
Friendly	37	3.70
Cheerful	37	3.70

Note: Ratings of KW=preference score of KW/N, N=10.

As illustrated in Table 4.8, it is noticeable that the highest rating of KW in sales and marketing is “independent”, whose preference scores is 47 with 4.70 percent of ratings. Based on Equation (74), the rating of “independent” obtained is demonstrated as $47/10 = 4.70$, where $n = 10$. This is then followed by “diligent”, with 46 preference scores, and it is 4.60 percent of ratings. The third favoured KWs in sales and marketing are “responsible” and “honest”. Both have the same 45 preference scores (4.50 percent of ratings). Meanwhile, Table 4.8 also shows that the least favoured of KWs in sales and marketing are “friendly” and “cheerful”. They have the lowest 37 preference scores (3.70 percent of ratings).

Table 4.9: Ratings of twenty of KWs for service.

Kansei Words	Preference Score	Ratings (%)
Responsible	44	4.40
Honest	43	4.30
Friendly	41	4.10
Diligent	41	4.10
Cooperative	41	4.10
Independent	40	4.00
Intuitive	39	3.90
Cost	39	3.90
Easy going	39	3.90
Confidence	39	3.90
Cheerful	38	3.80
Flexibility	38	3.80
Approachable	37	3.70
Efficient	37	3.70
Energetic	37	3.70
Patient	37	3.70
Experience	36	3.60
Curiosity	36	3.60
Punctuality	35	3.50
Procedural	34	3.40

Note: Ratings of KW=preference score of KW/N, N=10.

As Table 4.9 reports, it is cleared that the most preferred KW for service is “responsible” that has highest 44 preference scores with 4.40 percent of ratings. Based on Equation (74), the rating of “responsible” obtained is demonstrated as $44/10 = 4.40$, where $n = 10$. This is then followed by “honest”, whose preference score is 43 (4.30 percent of ratings). The third preferred KWs are “friendly”, “diligent” and “cooperative”. All have the same 41 preference scores (4.10 percent of ratings). Next, Table 4.9 also demonstrates the least preferred KW in service is “procedural”, whose preference score is only 34 at 3.40 percent of ratings. On the other hand, Figure 4.2 summaries the ratings of twenty KWs for all industries.

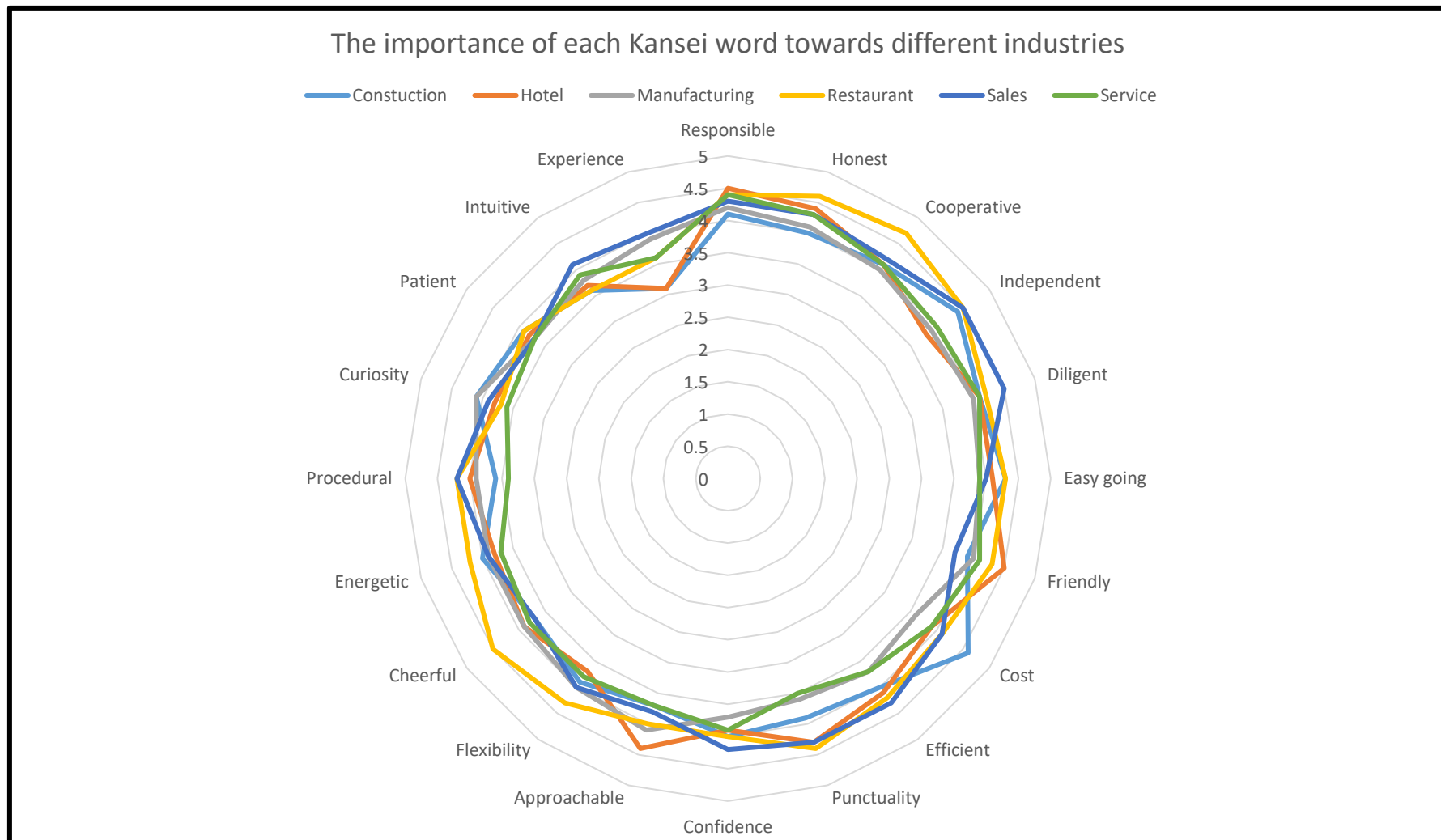


Figure 4.2: The importance of each KW towards different industries.

4.2 Discussion of Kansei Words in Different Unskilled Industries

Table 4.4 shows the ratings of twenty KWs for construction sector. It is clear that the KW “cost” is the most prominent whereas “experience” is the least relevant for construction sector. The construction employers normally need a large pool of unskilled workers for the positions like general workers. Therefore, the “cost” becomes the most prominent factor for employers to hire the unskilled workers in construction sector. The more workers that an employer hire, the more funds that the employer needs for the workers. The unskilled workers in construction sector do not need as much experience as the daily jobs due to the construction work, which requires the workers to be physically strong, is simple.

Based on Table 4.5, the most favorable KWs of hotel sector are “responsible” and “friendly” whereas the least preferable is “experience”. These results are similar as the overall results shown in Table 4.2. “Responsible” plays a vital role for unskilled workers in the hotel sector because it affects the sales and the reputation of a hotel. Irresponsible workers increase the complaint rate of hotel customers. On the other hands, “friendly” is a must for unskilled workers in hotels because they always need to show their friendliness to customers and colleagues. Apart from that, the “experience” is the least preferred as the daily job for unskilled workers in hotel is easy to learn. The unskilled workers can learn the required skills for the job in less than a day.

Table 4.6 shows the rankings of twenty KWs for manufacturing sector. Again, “responsible” is the most prominent KW but the “punctuality” is the least preferred KW for the manufacturing sector. In the manufacturing sector, daily tasks for unskilled workers is repetitive. Therefore, they need to be “responsible” in confirming their work being done in

a proper way without causing any problem for other departments. The “cost” and “punctuality” are the least preferred KWs as the salaries for unskilled workers who are from manufacturing sector are based on the total hours recorded in their own punch cards. Hence, the unskilled workers need to go to the workstation on time if they need to get the full amount of their salaries for that month. On the other hand, the pay rate of unskilled workers in manufacturing sector is standardised at around RM1000 to RM1187 per month (MIDA, 2015). Therefore, “cost” becomes the one of the least favourable KWs in manufacturing sector.

The most favorable KW as shown in Table 4.7 for restaurant workers is “cooperative” whereas the least preferred ones are “intuitive” and “experience”. The positions for unskilled workers in a restaurant are waiters, waitresses, food stall helpers, and cashiers. The “cooperative” is important for them as their jobs are connected to each other. Once the waiter or the waitress receives an order from customers, they need to pass the order to food stall helpers. Therefore, being “cooperative” with one another is important for the unskilled workers to work smoothly in a restaurant. Apart from that, “intuitive” and “experience” are not needed for restaurants as the unskilled workers can get a short-term training in the restaurants before they start working.

Based on Table 4.8, “independent” KW is the most prominent for sales workers but “friendly” and “cheerful” are the least preferable. The normal positions for unskilled workers in sales are promoters, merchandisers, cashiers, and cleaners. The “independent” becomes the most favourable as the employers need the unskilled workers to do their jobs

independently without the need to keep reminding them. For example, merchandisers need to keep uploading goods onto shelves if there is an empty space on the shelves.

Table 4.9 shows the most favorable KW in service sectors is “responsible” whereas the least preferable is “procedural”. The normal task of unskilled workers in the service sector is to serve customers. Hence, “responsible” is important as the workers need to do their jobs complete and well. Different customers have different characteristics, therefore, employers do not need their workers to follow a particular way to serve the customers.

In a nutshell, it can be concluded that “experience” is not a vital requirement for the unskilled job categories. Most of the employers are willing to accept the unskilled workers who do not have “experience” but he or she must be a “responsible” worker.

4.3 Evaluation of the Proposed System

A numerical example is named as Case Study A – Company A is applied to evaluate the proposed system and algorithm in the recruitment of unskilled workers. Recruitment of unskilled workers based on the consideration of twenty KWs which are “independent” (C1), “diligent” (C2), “responsible” (C3), “honest” (C4), “punctuality” (C5), “efficient” (C6), “cooperative” (C7), “confidence” (C8), “procedural” (C9), “intuitive” (C10), “friendly” (C11), “easy going” (C12), “experience” (C13), “energetic” (C14), “curiosity” (C15), “Approachable” (C16), “patient” (C17), “friendly” (C18), “cheerful” (C19), “cost” (C20). Twenty real candidates were provided by Company A. These candidates are named as A1 to A20 respectively.

In our evaluation, the decision-making group (DM) is formed by 5 human resource experts from Company A, namely D1 to D5. All experts from DM are working at human resource departments, such as the human resource manager and the recruit team in Company A. All have at least 3 years' experiences in recruiting employees in Company A.

This study applied the linguistic variables for criteria weight which are developed by Wang and Lee (2009) as shown in Figure 3.4 and Table 3.5. The triangular fuzzy number is used to express the importance of each criterion. The linguistic terms range from "very low" (VL) to 'very high" (VH). Apart from that, the linguistic term and fuzzy number is used to rate each alternative based on Figure 3.5 and Table 3.6 which are developed by Wang and Lee (2009). The triangular fuzzy number used to express the evaluation of each candidate. The linguistic terms range from "very poor" (VP) to "very good" (VG).

Each expert from DM group rates the criteria's weight with respect to the linguistic terms. All experts need to evaluate how important each criterion is during the recruitment of unskilled workers. The result is illustrated in Table 4.10. Next, Table 4.11 shows the evaluation on ideal alternatives. During the interview, five experts from DM group need to come to an agreement in normalising their own ideal alternatives' values into one final best value for each criterion which is then accepted by all 5 experts (Md Saad, Ahmad, Abu, & Jusoh, 2014). Additionally, all candidates' ratings based on C1 to C20 are recorded in Tables 28 and 29. The "A" represents "very good" (VG), the "E" represents "medium good" (MG), the "G" represents "good" (G), the "F" represents "fair", the "W" represents "medium poor" (MP), the "P" represents "poor" (P), and the "Z" represents "very poor" (VP) in Tables 28 and 29.

Table 4.10: Each criterion weight in linguistic term.

DMs	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20
D1	VH	VH	VH	VH	MH	H	H	M	H	ML	VH	M	L	H	MH	M	H	H	MH	M
D2	M	MH	VH	H	VH	H	H	MH	MH	M	M	ML	H	ML	ML	MH	H	H	MH	M
D3	MH	MH	H	VH	M	ML	ML	MH	M	M	MH	H	M	ML	ML	MH	H	L	MH	M
D4	M	MH	H	H	H	ML	M	ML	MH	MH	H	MH	ML	H	MH	MH	H	H	H	H
D5	MH	MH	VH	VH	MH	H	MH	MH	ML	ML	H	ML	L	MH	ML	ML	M	M	MH	M

Note: **VL** is very low, **L** is low, **ML** is medium low, **M** is medium, **MH** is medium high, **H** is high, and **VH** is very high.

Table 4.11: Ideal alternative.

Is	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20
I	G	G	A	A	G	G	G	E	G	E	A	G	E	G	E	G	G	G	G	L

Note: **Z** is very poor, **P** is poor, **W** is medium poor, **F** is fair, **E** is medium good, **G** is good, and **A** is very good.

Table 4.12: Alternative ratings based on C1 to C10.

DMs	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	GFFEE	WEFEE	GEEGE	AGEAE	EGGGE	EFEFE	WGWGE	FFWFE	EGFFE	GGWGE
A2	MFWWE	WEWWE	GEFFE	AGEGE	GGFGE	GFWFE	EGWGE	GPFWE	WGWWE	WEFEE
A3	EPWEW	GWWEW	GFPGF	AGFAF	AGWGF	AFPFW	FGPGF	GPPFF	GGWFF	GWFWF
A4	GEGEW	EGFEG	GGEGE	GGFAE	GAGGW	GGFGW	GGFFG	GGEFF	GGEEF	WGEWF
A5	GGGGG	EGGGW	GGGGG	GGEGW	WAGEW	GGGGW	GAGGF	GGGGF	GGFGG	GGWGF
A6	FGWGW	WGWGW	FGFGF	EGFGF	EAFEF	GGWGW	GAEGW	FGEFF	GGWGW	WGFGW
A7	GGEFG	GGGGF	GGEGB	AAEAG	GAFGF	EGEGF	GAEGG	WGEEF	GGWGF	FGFWF
A8	WEWWP	EGWWE	GGFGG	GGFGG	GAGWG	GGWFF	GGWGG	GWWWW	WGFWW	WWWWW
A9	FGFAE	GGFGE	GGFGG	GGFAG	GAFGG	GGFGG	GGWGG	GGWEG	EGWGG	WGWGF
A10	WGPWP	WGWWE	GGFGG	GGFAG	GAWFG	GGPFF	GGWFG	GFPPF	EGFWF	WWFPF
A11	FGGAG	WGFGF	GGEGB	GGEGB	WGEEF	EGFGF	GGFGG	FGFGG	EGFGF	FGWGF

Table 4.12 continued

A12	PGWGW	WGFWF	WGEEE	GGEEE	EGEEF	FGFGF	GGFWG	FGFWG	GGFFF	WGWFF
A13	PGGGG	WGEFG	EGEGG	EGEGE	WEEEE	FGEGE	FGEGE	FGEWG	GGFWF	FGFGF
A14	EGWAW	FGWGW	GGFGE	EGFAE	EEFGE	GGFEF	GGFFF	GGFFF	EGFGF	EGFGW
A15	GGGGG	FGFGE	GGEGG	FGEGE	GGEGE	GGFGF	GGFGF	GGFGG	GGFGF	GEFGW
A16	GWPGW	GWPGW	GFPGE	EGWGE	FFWEE	GGWGF	GEWGF	GGWGF	GEWGF	FFWGF
A17	GEWEG	GEWGG	GGFGF	GGFAF	GGGGF	GGFGF	GGFGF	GGFEF	GGFGF	GEFGF
A18	EEWGW	EEEGW	EGFGF	GGFGF	GGWGW	GGFGW	GGFGF	GGFGF	GGFGF	GEFGF
A19	EEWGW	GEEGW	GEFGE	GEFGF	GGWGF	FGFGF	FGFGF	WGFFF	EEFGF	FEFEF
A20	PWWWW	PWWWW	WGFGF	GGFGF	GFWFF	GWFFF	FGFFF	GGFFF	WGFGF	WWFGF

Note: **GFEEE** refers to first DM assigns **G**, second DM assigns **F**, third DM assigns **F**, forth DM assigns **E**, and fifth DM assigns **E**.

Table 4.13: Alternative ratings based on C11 to C20.

DMs	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	GFFAE	GAWGE	GEFFE	EGFEE	GFEEE	GGFEE	GGWGE	AGFGE	GGFFE	FFFLF
A2	GAFAE	GAWFE	GFFFE	FGEFE	GEWEE	GGWGE	GGWEE	AGFFE	GGFFE	WFFLF
A3	GGPAW	AGWFG	GFPFF	WEFFF	GEPFF	GGWFG	AEWGF	AGFFG	GGFFF	LFFFF
A4	GFFGF	GGFFG	AGGGF	GGEEW	FGWWW	EGFGW	GFFFW	GFFFG	GFFFG	FLFLF
A5	GGGGF	GGFGG	GGGGF	GGGGW	GEFGW	FGEEW	GGGGW	GGGAG	GGFAG	LLLLF
A6	EGFGF	EGFGF	FGGGF	GGFWW	WWFEW	WGWGE	GGWGE	FGFFE	EWFFE	LFFLF
A7	GGFGF	GGFGG	GGGFF	GGGFF	GGFFF	FGWGG	GGEGF	GGFAG	AGFAG	LFFLF
A8	FGPEF	GGWEG	GGFFF	EGFEG	FFPEF	FGFEG	GGFFG	GGFEG	GGFEG	FWFFF
A9	GWEGG	GGFEG	EGFGG	FGFWF	GGFGG	GGFGG	GWFGG	GGFFG	GGFFG	LLFFF
A10	FGPGF	GWWFG	GGFFG	EFGFG	FPPWF	EGFWG	GGGPG	GFEPF	GFEPG	FFFLF
A11	FGFGF	GGFGF	GGGGG	AEGGF	GEFEF	EGWGF	FGWGG	GGFAF	GEFGG	LLFLF
A12	FGEFF	FGEFF	AGGGG	GEGFF	WEFFF	WGEWF	FGEWG	FGFFF	FEFFF	LLFFF
A13	EGFFF	EEFFF	GGGGG	EEGEF	GGFWF	FGWEF	PFFFW	PGFFW	WGFFW	LFFLF
A14	GGWEF	GEWEF	GGWGF	WEFGW	WEFWW	WGFGF	FFFGE	FWFGE	FGFGE	LFFLF
A15	GGFGF	GEEGF	GGFGG	EEWGF	GGWGF	GGWGF	FGFGG	GGFAG	GGWAG	LFFLF

Table 4.13 continued

A16	GGPFF	GGFGF	AGFAF	GGPGF	GGFGF	GGFGF	GWFGF	GWFAE	GGFAE	WFFLF
A17	GAFGF	GGFGF	GGFAG	GGFGF	GEWGF	GGFGF	GGFGF	GGFAG	GGFAG	LFFLF
A18	GGFGF	GGFGF	GGEGB	GGEGF	GEWGE	GGFGE	GGFGG	GGFGG	GGFGG	LFFLF
A19	GGFGF	GGFGF	GGEGF	EGEGW	FGWGW	GEFGW	GEFGF	GGFGF	GGFAF	LFFLF
A20	FGFFF	GGFFF	FWWGF	EFPGW	FFWWF	WGWGW	GFWGF	GGFFF	GGFFF	LFFLF

*Note: **GFFAE** refers to first DM assigns **G**, second DM assigns **F**, third DM assigns **F**, fourth DM assigns **A**, and fifth DM assigns **E**.*

Based on Equations (67), the subjective weight and the interval of subjective weight based on $\alpha = 0$ and $\alpha = 0.5$, the result of subjective weight, and its interval based on both α values are shown in Table 4.14. Apart from that, projection values based on $\alpha = 0$ and $\alpha = 0.5$ are calculated by Equation (66), and listed in Table 4.15 and 4.16 respectively. While applying Shannon's entropy theory using Equations (68) to (71), objective weight is obtained and recorded in Table 4.17. As illustrated in Table 4.17, it is cleared that the "experience" (C13) is the most important criterion based on Shannon's entropy concept to recruit unskilled workers for Company A because it has the highest degree of diversification in both $\alpha = 0$ and $\alpha = 0.5$. The smaller the value of the entropy, then the higher the entropy weight. This shows the greater different alternatives in "experience" (C13). Therefore, this criterion can provide more information in the decision-making process.

Table 4.14: Subjective weight.

Criteria	Subjective Weight	Subjective Weight ($\alpha=0$)	Subjective Weight ($\alpha=0.5$)
C1	(0.5 , 0.66 , 0.78)	(0.5 , 0.78)	(0.58 , 0.72)
C2	(0.56 , 0.72 , 0.84)	(0.56 , 0.84)	(0.64 , 0.78)
C3	(0.74 , 0.92 , 0.98)	(0.74 , 0.98)	(0.83 , 0.95)
C4	(0.74 , 0.92 , 0.98)	(0.74 , 0.98)	(0.83 , 0.95)
C5	(0.56 , 0.72 , 0.84)	(0.56 , 0.84)	(0.64 , 0.78)
C6	(0.47 , 0.62 , 0.77)	(0.47 , 0.77)	(0.545 , 0.695)
C7	(0.47 , 0.62 , 0.77)	(0.47 , 0.77)	(0.545 , 0.695)
C8	(0.41 , 0.56 , 0.71)	(0.41 , 0.71)	(0.485 , 0.635)
C9	(0.44 , 0.59 , 0.74)	(0.44 , 0.74)	(0.515 , 0.665)
C10	(0.32 , 0.47 , 0.62)	(0.32 , 0.62)	(0.395 , 0.545)
C11	(0.59 , 0.75 , 0.87)	(0.59 , 0.87)	(0.67 , 0.81)
C12	(0.38 , 0.53 , 0.68)	(0.38 , 0.68)	(0.455 , 0.605)
C13	(0.26 , 0.41 , 0.56)	(0.26 , 0.56)	(0.335 , 0.485)
C14	(0.44 , 0.59 , 0.74)	(0.44 , 0.74)	(0.515 , 0.665)
C15	(0.32 , 0.47 , 0.62)	(0.32 , 0.62)	(0.395 , 0.545)
C16	(0.41 , 0.56 , 0.71)	(0.41 , 0.71)	(0.485 , 0.635)
C17	(0.59 , 0.74 , 0.89)	(0.59 , 0.89)	(0.665 , 0.815)
C18	(0.47 , 0.62 , 0.77)	(0.47 , 0.77)	(0.545 , 0.695)
C19	(0.53 , 0.68 , 0.83)	(0.53 , 0.83)	(0.605 , 0.755)
C20	(0.41 , 0.56 , 0.71)	(0.41 , 0.71)	(0.485 , 0.635)

Table 4.15: Projection value for $\alpha = 0$.

Criteria	D1	D2	D3	D4	D5
C1	0.2813	0.1563	0.2031	0.1563	0.2031
C2	0.2571	0.1857	0.1857	0.1857	0.1857
C3	0.2093	0.2093	0.186	0.186	0.2093
C4	0.2093	0.186	0.2093	0.186	0.2093
C5	0.1857	0.2571	0.1429	0.2286	0.1857
C6	0.2581	0.2581	0.1129	0.1129	0.2581
C7	0.2581	0.2581	0.1129	0.1613	0.2097
C8	0.1786	0.2321	0.2321	0.125	0.2321
C9	0.2712	0.2203	0.1695	0.2203	0.1186
C10	0.1489	0.2128	0.2128	0.2766	0.1489
C11	0.2466	0.137	0.1781	0.2192	0.2192
C12	0.1887	0.1321	0.3019	0.2453	0.1321
C13	0.0976	0.3902	0.2439	0.1707	0.0976
C14	0.2712	0.1186	0.1186	0.2712	0.2203
C15	0.2766	0.1489	0.1489	0.2766	0.1489
C16	0.1786	0.2321	0.2321	0.2321	0.125
C17	0.2162	0.2162	0.2162	0.2162	0.1351
C18	0.2581	0.2581	0.0645	0.2581	0.1613
C19	0.1912	0.1912	0.1912	0.2353	0.1912
C20	0.1786	0.1786	0.1786	0.2857	0.1786

Table 4.16: Projection value for $\alpha = 0.5$.

Criteria	D1	D2	D3	D4	D5
C1	0.2923	0.1538	0.2	0.1538	0.2
C2	0.2676	0.1831	0.1831	0.1831	0.1831
C3	0.2135	0.2135	0.1798	0.1798	0.2135
C4	0.2135	0.1798	0.2135	0.1798	0.2135
C5	0.1831	0.2676	0.1408	0.2254	0.1831
C6	0.2581	0.2581	0.1129	0.1129	0.2581
C7	0.2581	0.2581	0.1129	0.1613	0.2097
C8	0.1786	0.2321	0.2321	0.125	0.2321
C9	0.2712	0.2203	0.1695	0.2203	0.1186
C10	0.1489	0.2128	0.2128	0.2766	0.1489
C11	0.2568	0.1351	0.1757	0.2162	0.2162
C12	0.1887	0.1321	0.3019	0.2453	0.1321
C13	0.0976	0.3902	0.2439	0.1707	0.0976
C14	0.2712	0.1186	0.1186	0.2712	0.2203
C15	0.2766	0.1489	0.1489	0.2766	0.1489
C16	0.1786	0.2321	0.2321	0.2321	0.125
C17	0.2162	0.2162	0.2162	0.2162	0.1351
C18	0.2581	0.2581	0.0645	0.2581	0.1613
C19	0.1912	0.1912	0.1912	0.2353	0.1912
C20	0.1786	0.1786	0.1786	0.2857	0.1786

Table 4.17: Shannon's Entropy based weight.

Criteria	Entropy Value		Degree of Diversification		Objective Weight	
	$\alpha = 0$	$\alpha = 0.5$	$\alpha = 0$	$\alpha = 0.5$	$\alpha = 0$	$\alpha = 0.5$
C1	0.9844	0.9812	0.0156	0.0188	0.0156	0.0401
C2	0.9941	0.9918	0.0059	0.0082	0.0059	0.0176
C3	0.999	0.9979	0.001	0.0021	0.001	0.0046
C4	0.999	0.9979	0.001	0.0021	0.001	0.0046
C5	0.9879	0.9856	0.0121	0.0144	0.0121	0.0306
C6	0.9576	0.9576	0.0424	0.0424	0.0424	0.0905
C7	0.9738	0.9738	0.0262	0.0262	0.0262	0.056
C8	0.9846	0.9846	0.0154	0.0154	0.0154	0.0329
C9	0.9781	0.9781	0.0219	0.0219	0.0219	0.0467
C10	0.9825	0.9825	0.0175	0.0175	0.0175	0.0374
C11	0.988	0.9863	0.012	0.0137	0.012	0.0293
C12	0.9666	0.9666	0.0334	0.0334	0.0334	0.0713
C13	0.9117	0.9117	0.0883	0.0883	0.0883	0.1886
C14	0.9611	0.9611	0.0389	0.0389	0.0389	0.083
C15	0.9704	0.9704	0.0296	0.0296	0.0296	0.0632
C16	0.9846	0.9846	0.0154	0.0154	0.0154	0.0329
C17	0.991	0.991	0.009	0.009	0.009	0.0192
C18	0.9443	0.9443	0.0557	0.0557	0.0557	0.1189
C19	0.9977	0.9977	0.0023	0.0023	0.0023	0.005
C20	0.987	0.987	0.013	0.013	0.013	0.0278

The distance values within fuzzy positive ideal solution and fuzzy negative ideal solution, and closeness coefficients for each candidate are computed based on F-TOPSIS by the Equations (28) and (33). The results are reported in Table 4.18. Meanwhile, the distance values between ideal alternatives with other candidates are calculated based on hamming distance method using Equations (72) and (73). The results of distance value based on hamming distance method are listed in Table 4.19.

Table 4.18: F-TOPSIS closeness coefficient.

Alternative	d+	d-	Closeness Coefficient
A1	7.1716	6.106	0.4599
A2	7.4455	5.5448	0.4268
A3	7.7016	5.0907	0.398

Table 4.18 continued

A4	7.3041	6.0342	0.4524
A5	6.3754	7.1668	0.5292
A6	7.4608	5.4727	0.4231
A7	6.8364	6.7469	0.4967
A8	7.7557	5.5062	0.4152
A9	6.8975	6.5913	0.4887
A10	8.0104	5.1413	0.3909
A11	6.8753	6.421	0.4829
A12	7.5239	5.4286	0.4191
A13	7.6217	5.572	0.4223
A14	7.4855	5.618	0.4287
A15	6.8818	6.6277	0.4906
A16	7.2733	5.5547	0.433
A17	6.744	6.5582	0.493
A18	6.7588	6.3793	0.4856
A19	7.2298	5.8803	0.4485
A20	8.1357	4.6673	0.3645

Table 4.19: Distance value based on Hamming Distance method with subjective weight and objective weight.

Alternative	Subjective Weight		Objective Weight	
	$\alpha = 0$	$\alpha = 0.5$	$\alpha = 0$	$\alpha = 0.5$
A1	0.0955	0.1005	0.2339	0.2359
A2	0.1196	0.1249	0.3094	0.3136
A3	0.1421	0.1465	0.3991	0.3993
A4	0.0996	0.1063	0.2901	0.2973
A5	0.059	0.0657	0.1477	0.1541
A6	0.1233	0.1303	0.312	0.3182
A7	0.0635	0.0676	0.1648	0.166
A8	0.123	0.1298	0.315	0.3234
A9	0.0778	0.0838	0.2196	0.2226
A10	0.1399	0.1464	0.4009	0.408
A11	0.0849	0.0914	0.2396	0.2409
A12	0.1306	0.1386	0.377	0.387
A13	0.124	0.1315	0.3609	0.3652
A14	0.115	0.1216	0.3123	0.3178
A15	0.0764	0.0829	0.2066	0.2082
A16	0.1238	0.1314	0.2942	0.3106
A17	0.0759	0.0818	0.2009	0.2077
A18	0.0863	0.094	0.2195	0.2285
A19	0.1052	0.1124	0.2716	0.2786
A20	0.1604	0.1685	0.4531	0.4644

Additionally, the rankings of alternatives based on F-TOPSIS, hamming distance method and experts from decision-making groups are recorded in Table 4.20. As demonstrated in Table 4.20, the order of top five ratings among all alternatives based on F-TOPSIS is $A5 > A7 > A17 > A15 > A9$. It is clear to show that A5 is the best candidate who will be recommended by F-TOPSIS to be selected during recruitment of the unskilled worker. The higher the closeness coefficient, then the better the alternative to be chosen in F-TOPSIS. Therefore, the A5 is considered the best candidate based on F-TOPSIS calculation.

Table 4.20: Ranking of alternative based on Hamming Distance method, F-TOPSIS and experts.

Ranking	Hamming Distance Method				F-TOPSIS	Experts
	Subjective Weight		Objective Weight			
	$\alpha =0$	$\alpha =0.5$	$\alpha =0$	$\alpha =0.5$		
1	A 5	A 5	A 5	A 5	A 5	A 5
2	A 7	A 7	A 7	A 7	A 7	A 17
3	A 17	A 17	A 17	A 17	A 17	A 7
4	A 15	A 15	A 15	A 15	A 15	A 15
5	A 9	A 9	A 18	A 9	A 9	A 18
6	A 11	A 11	A 9	A 18	A 18	A 9
7	A 18	A 18	A 1	A 1	A 11	A 11
8	A 1	A 1	A 11	A 11	A 1	A 2
9	A 4	A 4	A 19	A 19	A 4	A 14
10	A 19	A 19	A 4	A 4	A 19	A 16
11	A 14	A 14	A 16	A 16	A 16	A 19
12	A 2	A 2	A 2	A 2	A 14	A 4
13	A 8	A 8	A 6	A 14	A 2	A 1
14	A 6	A 6	A 14	A 6	A 6	A 12
15	A 16	A 16	A 8	A 8	A 13	A 13
16	A 13	A 13	A 13	A 13	A 12	A 6
17	A 12	A 12	A 12	A 12	A 8	A 8
18	A 10	A 10	A 3	A 3	A 3	A 3
19	A 3	A 3	A 10	A 10	A 10	A 10
20	A 20	A 20	A 20	A 20	A 20	A 20

Note: **Highlighted** indicates the top five alternatives from different approaches.

Meanwhile, the top five rated among all alternatives based on hamming distance method

are shown (subjective weight with $\alpha = 0$ and 0.5) is $A5 > A7 > A17 > A15 > A9$. It is clear to show that the A5 is the best candidate who will be recommended by hamming distance method in subjective weight with both $\alpha = 0$ and 0.5. Apart from that, the order of top five ratings among all alternatives based on hamming distance method (objective weight with $\alpha = 0$) is $A5 > A7 > A17 > A15 > A18$, and the order of top five ratings among all alternatives based on hamming distance method (objective weight with $\alpha = 0.5$) is $A5 > A7 > A17 > A15 > A9$. Therefore, again, the best candidate is still A5 who is recommended based on hamming distance method during recruitment of the unskilled worker. The less distance value in hamming distance method is considered as the preferred candidate to be selected.

Lastly, the results from both F-TOPSIS and hamming distance method are similar to the rankings of alternatives which are provided by experts from a DM group. The rankings of alternatives based on experts from decision-making group is $A5 > A17 > A7 > A15 > A18$. Therefore, the A5 is still the best candidate to be recommended and selected by the proposed system.

Apart from that, Table 4.21 shows the top ten shortlisted alternatives based on different approaches. From Table 4.21, it can clearly illustrate the alternative who is in the top ten shortlisted alternatives with 1 (“yes”), and for those alternatives who are not in the top ten alternatives with 0 (“no”).

Table 4.21: Top ten shortlisted alternative based on different approaches

Alternative	Hamming Distance Method				F-TOPSIS	Experts
	Subjective Weight		Objective Weight			
	$\alpha =0$	$\alpha =0.5$	$\alpha =0$	$\alpha =0.5$		
A1	1	1	1	1	1	0
A2	0	0	0	0	0	1
A3	0	0	0	0	0	0
A4	1	1	1	1	1	0
A5	1	1	1	1	1	1
A6	0	0	0	0	0	0
A7	1	1	1	1	1	1
A8	0	0	0	0	0	0
A9	1	1	1	1	1	1
A10	0	0	0	0	0	0
A11	1	1	1	1	1	1
A12	0	0	0	0	0	0
A13	0	0	0	0	0	0
A14	0	0	0	0	0	1
A15	1	1	1	1	1	1
A16	0	0	0	0	0	1
A17	1	1	1	1	1	1
A18	1	1	1	1	1	1
A19	1	1	1	1	1	0
A20	0	0	0	0	0	0

Note: **1** indicates “YES” for the alternative who is in top ten shortlisted alternatives, **0** refers “NO” for the alternatives who is not in top ten shortlisted alternatives.

Appendix B illustrates the contingency table for top ten shortlisted alternatives between proposed solution and hamming distance based on subjective weight and objective weight when $\alpha = 0$ and $\alpha = 0.5$. From Appendix B, based on Equation (74), the relative observed agreement among raters, P_0 is calculated as $(1 + 0 + 0 + 1 + 1 + 0 + 1 + 0 + 1 + 0 + 1 + 0 + 0 + 0 + 1 + 0 + 1 + 1 + 1 + 0)/10 = 1$, meanwhile, based on Equation (78), the hypothetical probability of chance agreement, P_e is demonstrated as $(0.1 \times 0.1) + 0 + 0 + (0.1 \times 0.1) + (0.1 \times 0.1) + 0 + 0 + (0.1 \times 0.1) + 0 + (0.1 \times 0.1) + 0 + 0 + 0 + (0.1 \times 0.1) + 0 + (0.1 \times 0.1) + (0.1 \times 0.1) + (0.1 \times 0.1) + 0 = 0.1$. As a

result, Cohen's Kappa K , which is calculated based on Equation (79), is demonstrated as $(1 - 0.1)/(1 - 0.1) = 1$. Based on the degree of agreement of Cohen's Kappa Coefficient, the inter-rater reliability among two raters, proposed solution and hamming distance method is satisfying because the obtained Cohen's Kappa, K is 1 which is greater than 0.7 (Fleiss, Levin, & Paik, 2013).

Additionally, Appendix C shows the contingency table for top ten shortlisted alternatives between proposed solution and experts. From Appendix C, based on Equation (74), the relative observed agreement among raters, P_o is calculated as $(0 + 0 + 0 + 0 + 1 + 0 + 1 + 0 + 1 + 0 + 1 + 0 + 0 + 0 + 1 + 0 + 1 + 1 + 0 + 0)/10 = 0.7$, meanwhile, based on Equation (78), the hypothetical probability of chance agreement, P_e is demonstrated as $0 + 0 + 0 + 0 + (0.1 \times 0.1) + 0 + (0.1 \times 0.1) + 0 + (0.1 \times 0.1) + 0 + (0.1 \times 0.1) + 0 + 0 + 0 + (0.1 \times 0.1) + 0 + (0.1 \times 0.1) + (0.1 \times 0.1) + 0 + 0 = 0.07$. As a result, Cohen's Kappa K , which is calculated based on Equation (79), is demonstrated as $(0.7 - 0.07)/(1 - 0.07) = 0.7$. Based on the degree of agreement of Cohen's Kappa Coefficient, the inter-rater reliability among two raters, proposed solution and experts is satisfying because the obtained Cohen's Kappa, K is 0.7, which is between 0.6 and 0.8 (Fleiss, Levin, & Paik, 2013).

Table 4.22 summarises the result of Cohen's Kappa Coefficient for both inter-rater agreement between proposed solution and hamming distance method, and inter-rater agreement between proposed solution and experts.

Table 4.22: Summary of Cohen's Kappa Coefficient

Cohen's Kappa	F-TOPSIS VS Hamming Distance	F-TOPSIS VS Experts
P_0	1	0.7
P_e	0.1	0.07
K	1	0.7
Degree of Agreement	Excellent (Satisfaction)	Good (Satisfaction)

Note: P_0 indicates relative observed agreement among raters, and P_e indicates hypothetical probability of chance agreement

4.4 Conclusion

In conclusion, define criteria for recruitment of unskilled workers based on the personality traits with the Kansei Engineering, and applied the F-TOPSIS algorithm to calculate the better closeness coefficient to recommend the best candidate for the recruitment can be used to recruit the unskilled workers without any resume or cover letter. Based on the results of ratings of twenty KWs for all industries as illustrated in Table 4.3, it can concluded that different unskilled job sectors have different requirements of desired unskilled workers for their own working tasks. For example, recruiters from construction sector emphasises more on “cost” but they do not focus on “experience”, on contrary, recruiters from manufacturing sector focuses more on “responsible” than “cost”. Additionally, KW “responsible” represents the most popular, favourable and preferable KW among all KWs during recruitments of unskilled workers. There are three out of six unskilled job sectors select “responsible” as the most prominent KW. On the other hand, KW “experience” shows the least favourable and preferable KW among all KWs during recruitments of unskilled workers. There are three out of six unskilled job sectors choose “experience” as the least preferred KW. Hence, most unskilled employers are willing to accept the unskilled workers who do not have “experience” but he or she must be a “responsible” worker.

Apart from that, according to results of the case study A- Company A, as illustrated in Table 4.20, it can be concluded that applying F-TOPSIS algorithm to calculate the better closeness coefficient is suitable to recommend the best candidate for recruitments of unskilled workers. From Table 4.20, alternative A5 is the best alternative who is recommended by F-TOPSIS, hamming distance method, and human resource experts from Company A. Based on the result from Table 4.22, recommendation results from Table 4.20 have excellent and satisfying degree of agreement for both inter-rater agreement between F-TOPSIS and hamming distance method, and inter-rater agreement between F-TOPSIS and experts. Thus, it can be concluded that F-TOPSIS algorithm is suitable to recommend the best candidate for recruitments of unskilled workers because the reliability of between F-TOPSIS and hamming distance method, or between F-TOPSIS and experts from Company A is high, which has 1 and 0.7 for Cohen's Kappa coefficient respectively. Based on Fleiss, Levin and Paik (2013), inter-rater reliability among two raters is satisfying if and only if it obtained Cohen's Kappa, K greater than 0.7. Therefore, the recommendation results by F-TOPSIS are strongly agreed and supported by Cohen's Kappa coefficient.

CHAPTER 5

IMPLEMENTATION OF RECRUITMENT SELECTION SYSTEM

5.0 Introduction

This chapter introduces the implementation of the proposed system. It consists of the graphic user interfaces and the descriptions for each feature in the proposed system. All graphic user interfaces of proposed system is designed based on Shneiderman's Eight Golden Rules (O'Regan, 2018). Being illustrated in Figure 3.3, the architecture of the proposed system was constructed based on based on the integrated architecture for candidate filtering components which are adapted by Laumer and Eckhardt (2009) in Figure 2.3. In Figure 3.3, we used different colours to indicate the five distinct components of the system. The accent orange colour indicates employers whereas the green colour indicates job seekers. Next, the accent gold colour implies the F-TOPSIS subsystem which is the main component of this research, and the accent blue colour denotes other subsystems in this proposed system. Lastly, the light blue colour manifests the database. Furthermore, the entity relationship diagram of the proposed system is showed in Figure 3.2. In Figure 3.2, it clearly shows that there are seven tables to store different information for the job seekers and the recruiters: (a) authenticate user table is used to store all the authenticate users' details, (b) job seeker table is used to store all job seekers' details, (c) job seeker fuzzy rating table is used to store job seekers' rating scores, (d) employer table is used to store all recruiters' details, (e) job post table is used to store all job offers' details from recruiters, (f) job post fuzzy weight table is used to store all importance weight of each criterion for a particular job offers, (g) job applications table is used to store all applications from job seekers for particular job offers.

The proposed system was developed by using web programming language such as PHP, MYSQL and JAVASCRIPT.

5.1 User Graphic Interface

The design of proposed system fulfil all the Shneiderman's Eight Golden Rules (O'Regan, 2018).

i. Strive for consistency

All icons, colours, navigation menu items, call-to-actions, and the whole user flows are designed in the alike and similar situation, and arrangement of actions. This standardize layouts and call-to-actions is important in consistency which assist user become familiar and operate the user interface easily.

ii. Shortcut

Few shortcuts are provided in the proposed system, such as the home navigation icon, global search function, and navigation menu in the proposed system. These shortcut allows user to navigate and achieve their goals more quickly, easily and effortlessly.

iii. Informative feedback

The proposed system provides and offers informative feedback for each of the call-to-action, such as job application function. Job seekers will get notice after they submit the job application form, either successful or failed message. This human-readable feedback indicates and informs the users about the status of their call-to-actions process in the proposed system.

iv. Dialogue

The proposed system provides all the informative feedback in dialogue format which allows users to read the message easily after completed the call-to-actions.

v. Simple error handling

The proposed system provides simple instructions to tell the users about solutions for each error occurs. For example, popping out alert dialogue to inform the user the text fields is required to fill in if users forget to provide the input in the application form.

vi. Easy reversal of actions

The proposed system provides easy reversal of actions that allow users to undo the call-to-actions. For example, users can undo the delete actions of job applications lists in the proposed system.

vii. Support internal locus of control

The proposed system allows users to have the sense of full control of all the functions in the whole system.

viii. Reduce short-term memory load

The proposed system provides simple design of the whole system. These simple design allows users to recognize the functions easily without having to memorise each and every step, such as they click on the job apply button in order to apply for the job without having to remember each and every step to apply for the job. Due to the simplicity of user interface, it shows the recognition over recall.

Figure 5.1 shows the homepage of the proposed system. On the homepage, there are three navigation menu buttons that allow users to navigate to login page, register page, meanwhile, employers can use employer button (in green colour) to navigate to employer homepage. On the other hand, there is one image slider section to show the job advertisements.

Figure 5.2 shows the job seeker's login page. In this page, there are six navigation menu buttons that allow users to navigate to login page, register page, homepage, company profile, job seeker's own profile, and employers can use employer button (in green colour) to navigate to employer homepage. On the other hand, there is a login form in the central of the page which can allow users to submit their login email address and password to log into main page of the proposed system. Additionally, there is a quick search box above the login form which allows users to search the jobs by entering the keywords of job titles or company names.



Image Sliders

Sales and Marketing

professionals are in high demand.

Start applying today and make your next career move because you never know what's in store for you.



Figure 5.1: Homepage.

The screenshot shows the login page of the 'Unskilled Job Portal'. At the top, a blue navigation bar contains links for 'Home', 'Company Profile', and 'My Profile' (grouped in a red box), a central 'Navigation menu' (in a red box), and links for 'Login' and 'Register' (grouped in a red box). Below the navigation bar, the site logo 'J Unskilled Job Portal' is on the left. A search bar with a 'Search' button is highlighted with a green box and labeled 'Quick Seach Box'. To the right of the search bar is an 'Employer' button, also highlighted with a green box. The main content area features a 'Candidate Login' section, which is outlined in orange and labeled 'Login Form'. This section includes the text 'Find jobs matching your salary', an email input field with the placeholder 'Enter your email here', a password input field with the placeholder 'Enter your password here', a 'Remember Me' checkbox, and a 'Forgot Password ?' link. A prominent yellow 'Login' button is at the bottom of the form. Below the button, there is a link for 'New User? Sign Up for Free Now!' and a disclaimer: 'By connecting to Unskilled Job Portal, I have read and agreed to JobStreet.com Terms of Use and Privacy Policy.'

Figure 5.2: Job seeker's login page.

Figure 5.3 and 5.4 show the job seekers' registration page. In both registration pages, there are seven navigation menu buttons that allow users to navigate to login page, register page, homepage, company profile, job seeker's own profile, job seeker's job application, and employers can use employer button (in green colour) to navigate to employer homepage. The registration form (central of the registration page) which is from register page one allows users to submit their details such as username, email address, password, full name and password before entering into registration page two. On the other hand, the registration form (at the central of the registration page) which is from register page one allows user to enter their own rating scores based on each KW by using linguistic terms. Additionally, there is a quick search box above the registration form in both registration pages which allows users to search the jobs by entering the keywords of job titles or company names.

Figure 5.5 shows the job seeker's main page after users (job seekers) successfully log in by entering the correct email addresses and passwords. In this main page, there are five navigation menu buttons that allow users to navigate to main page, company profile page, job seeker's own profile page, job application page, and employers can use employer button (in green colour) to navigate to employer homepage. On the other hand, there is a quick search box above the main content of the main page which allows users to search the jobs by entering the keywords of job titles or company names. In the main content section, there is a user's details section to show important details of users such as name, age, I/C number, phone number and email address. There is job recommendation components which is able to show the recommendation jobs for users. Users can use the apply button to apply for jobs. On the right hand side of the main content section, there are two advertisement sections to show the top companies' logo's and sponsors' logo's.

Home Company Profile My Profile My Job Application

Navigation Menu

Login Register

Unskilled Job Portal Search Search

Employer

Quick Search Box

Candidate Sign Up

- ✓Stay connected with relevant career opportunities
- ✓Get jobs that are more relevant to you delivered daily
- ✓Let employers with the right jobs find you

Please Enter Your Personal Details Below:

Nickname

Email

Password

Confirm Password

Full Name in I/C

I/C Number

Registration Form One: Personal Details

Figure 5.3: Job seeker's registration page one.

[Home](#)
[Company Profile](#)
[My Profile](#)
[My Job Application](#)

[Login](#)
[Register](#)

Unskilled Job Portal

Quick Search Box

Candidate Sign Up

Please rate yourself according to different Kansei Word:

Linguistic Value	Very Poor	Poor	Medium Poor	Fair	Medium Good	Good	Very Good
Value	1	2	3	4	5	6	7
1) Independent					★ ★ ★ ★ ★ ★ ★	7	
2) Diligent					★ ★ ★ ★ ★ ★ ★	7	
3) Responsible					★ ★ ★ ★ ★ ★ ★	7	
4) Honest					★ ★ ★ ★ ★ ★ ★	7	
5) Punctuality					★ ★ ★ ★ ★ ★ ★	7	

Registration Form One: Personal Details

Figure 5.4: Job seeker's registration page two.

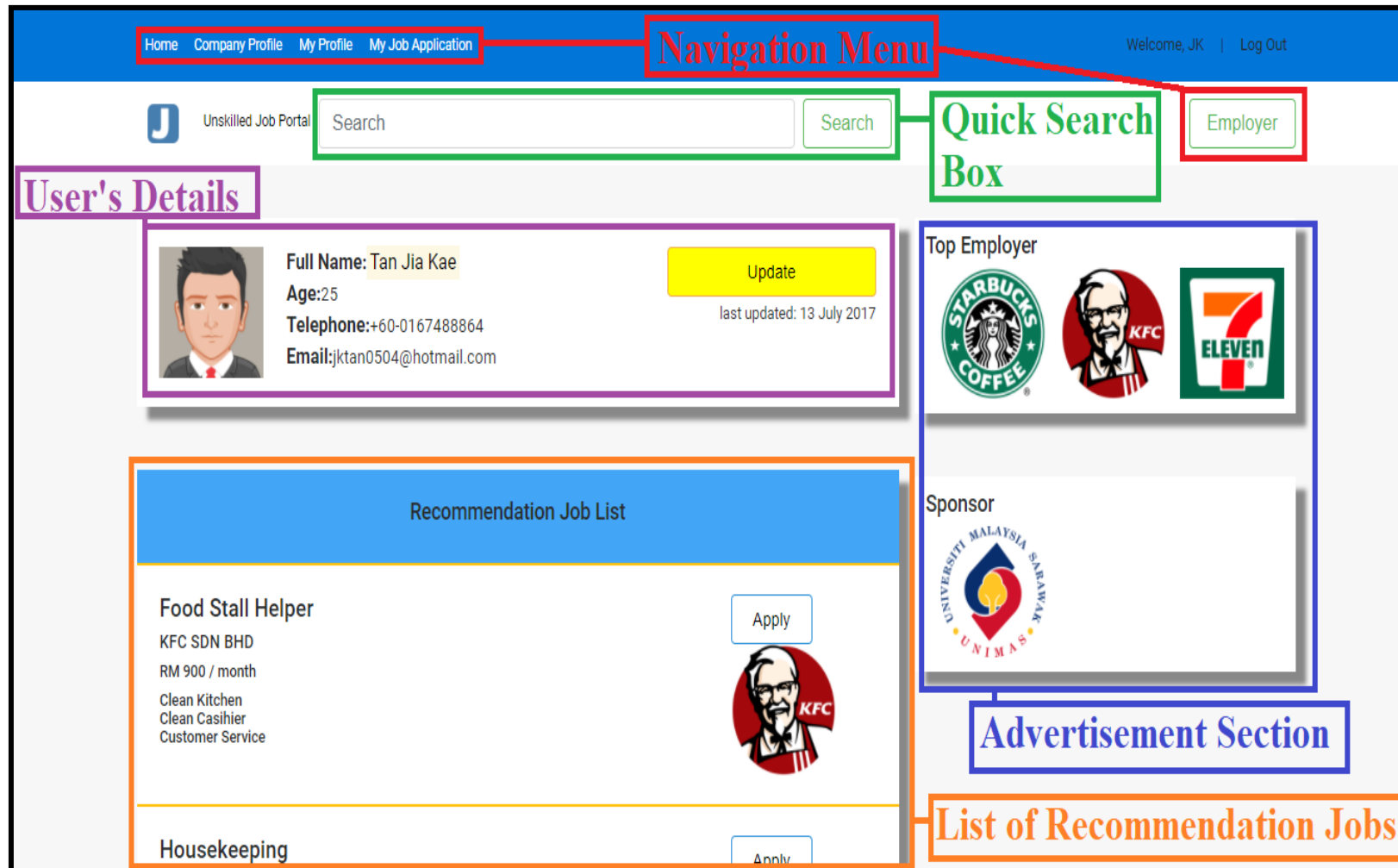


Figure 5.5: Job seeker's main page.

Figure 5.6 shows the job seekers' company profile page. This page has the same navigation menu buttons, quick search box feature and two advertisement sections on the right side of page like job seekers' main page in Figure 5.5. The main difference of this job seekers' company profile page is that there is a company profile details section located at the left of the page. In the company profile details section, it displays the company name, the company logo, the company description and the company rating scores.

Figure 5.7 shows the job seekers' own profile page. This page has the same navigation menu buttons, quick search box feature and two advertisement sections on the right side of page like job seekers' main page in Figure 5.5. The main difference of this job seeker's own profile page is that there is a user's profile form located at the left of the page. In the user's profile form, it allows users to update their own users' details in the proposed system, such as username and telephone number.

Figure 5.8 shows shows the job seekers' job application page. This page has the same navigation menu buttons, quick search box feature and two advertisement sections on the right side of page like job seeker's main page in Figure 5.5. The main difference of this job seeker's job application page is that there is a list of job applications located at the left of the page. In the list of job applications, it allows users to check the status of each job application.

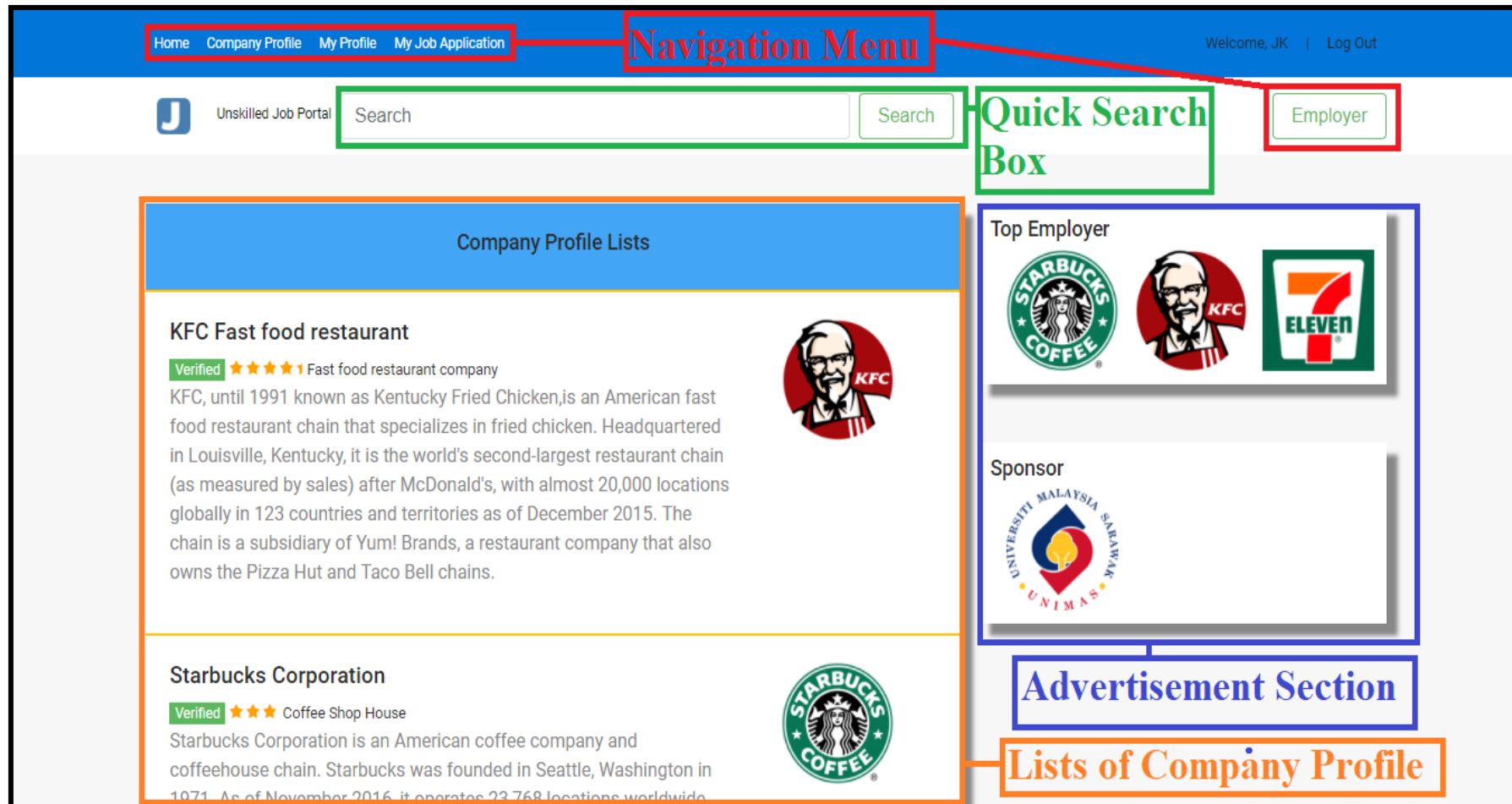


Figure 5.6: Job seeker's company profile page.

[Home](#) [Company Profile](#) [My Profile](#) [My Job Application](#)

Welcome, JK | [Log Out](#)

Unskilled Job Portal

Search

Search

Quick Search Box

Employer

My Personal Details



Change

Name

Tan Jia Kae

Age

25

Telephone

+60-0167488864

Username

JK

Password

Description

I am a very hardworking and responsible worker.

Update

Top Employer



Sponsor



Advertisement Section

Personal Details Form

Figure 5.7: Job seeker's own profile page.

[Home](#) [Company Profile](#) [My Profile](#) [My Job Application](#)

Welcome, JK | [Log Out](#)

Unskilled Job Portal

Search

Search

Quick Search Box

Employer

My Job Applications Details

No	Job Title	Company Name	Application Date	Status	Action
1	Food Stall Helper	KFC	7 August 2017	Pending	X
2	Waiter	Starbuck	10 June 2017	Rejected	X
3	Housekeeping	Self Employment	10 May 2016	Accepted	X

Lists of Job Application.

Top Employer



Sponsor



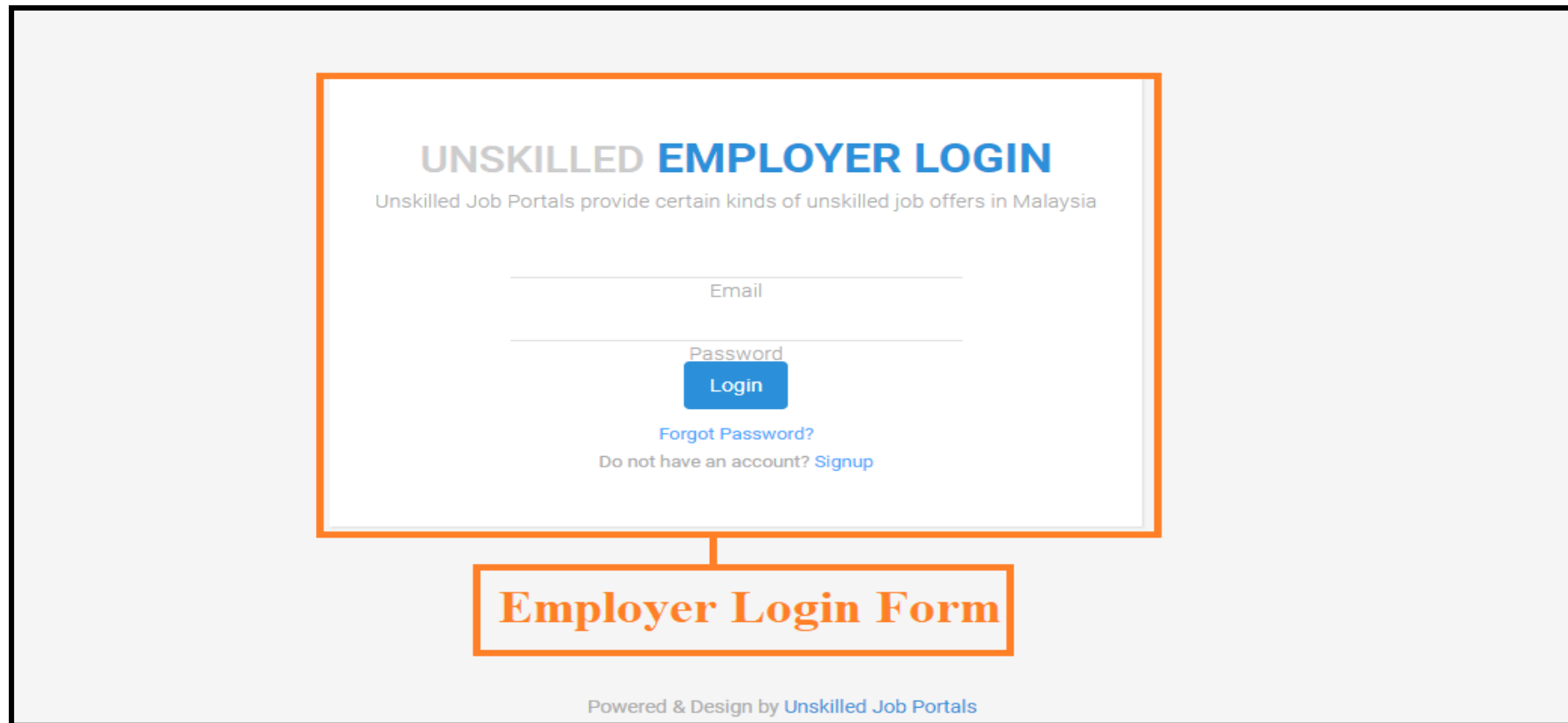
Advertisement Section

Figure 5.8: Job seeker's job application page.

Figure 5.9 shows the employer's login page. There is a login form in the middle of the page. This login form allows employers to enter their email addresses and passwords to log into the proposed system.

Figure 5.10 shows the employer's registration page. There is a registration form in the middle of the page. This registration form allows employers to enter their companies' details such as company names, usernames, email addresses and passwords to register their company account in the proposed system.

Figure 5.11 shows the employer's dashboard page. This is the main page for employers after they successfully log into the proposed system. There are five navigation menu buttons on the left sidebar of the page. This left sidebar navigation menu allows employers to navigate to dashboard page, job submit page, my company page, my job posts page and my invitation page. The main content of the dashboard shows the recruitment reports, the new applications, the new job posts, the remaining job vacancies, and the closed jobs.



The diagram illustrates the layout of an employer login page. It features a central white rectangular area with an orange border containing the login form. Below this area, a separate orange-bordered box contains the title 'Employer Login Form', which is connected to the form area by a vertical line. The footer of the page is a light gray bar with the text 'Powered & Design by Unskilled Job Portals'.

UNSKILLED EMPLOYER LOGIN

Unskilled Job Portals provide certain kinds of unskilled job offers in Malaysia

Email

Password

Login

[Forgot Password?](#)

Do not have an account? [Signup](#)

Employer Login Form

Powered & Design by [Unskilled Job Portals](#)

Figure 5.9: Employer's login page.

The image shows a web page layout for an employer's registration form. The page is enclosed in a black border. On the right side, there is a light gray vertical bar. Within this bar, an orange-bordered box contains the text "Employer Registration Form" in orange. A horizontal orange line connects this box to the left side of the main form area. The main form area is a white rectangle with an orange border. At the top of this area, the text "UNSKILLED EMPLOYER SIGN UP" is displayed in blue, with "UNSKILLED" in gray and "EMPLOYER SIGN UP" in blue. Below this, a subtitle reads "Unskilled Job Portals provide certain kinds of unskilled job offers in Malaysia". The form contains several input fields, each with a label above it: "User Name", "Company Email Address", "password", "Company Name", "Company Register Number", "Address Street", and "Address Street Line 2". The "password" and "Company Register Number" fields are highlighted with a thick yellow underline.

UNSKILLED EMPLOYER SIGN UP
Unskilled Job Portals provide certain kinds of unskilled job offers in Malaysia

User Name

Company Email Address

password

Company Name

Company Register Number

Address Street

Address Street Line 2

Employer Registration Form

Figure 5.10: Employer's registration page.

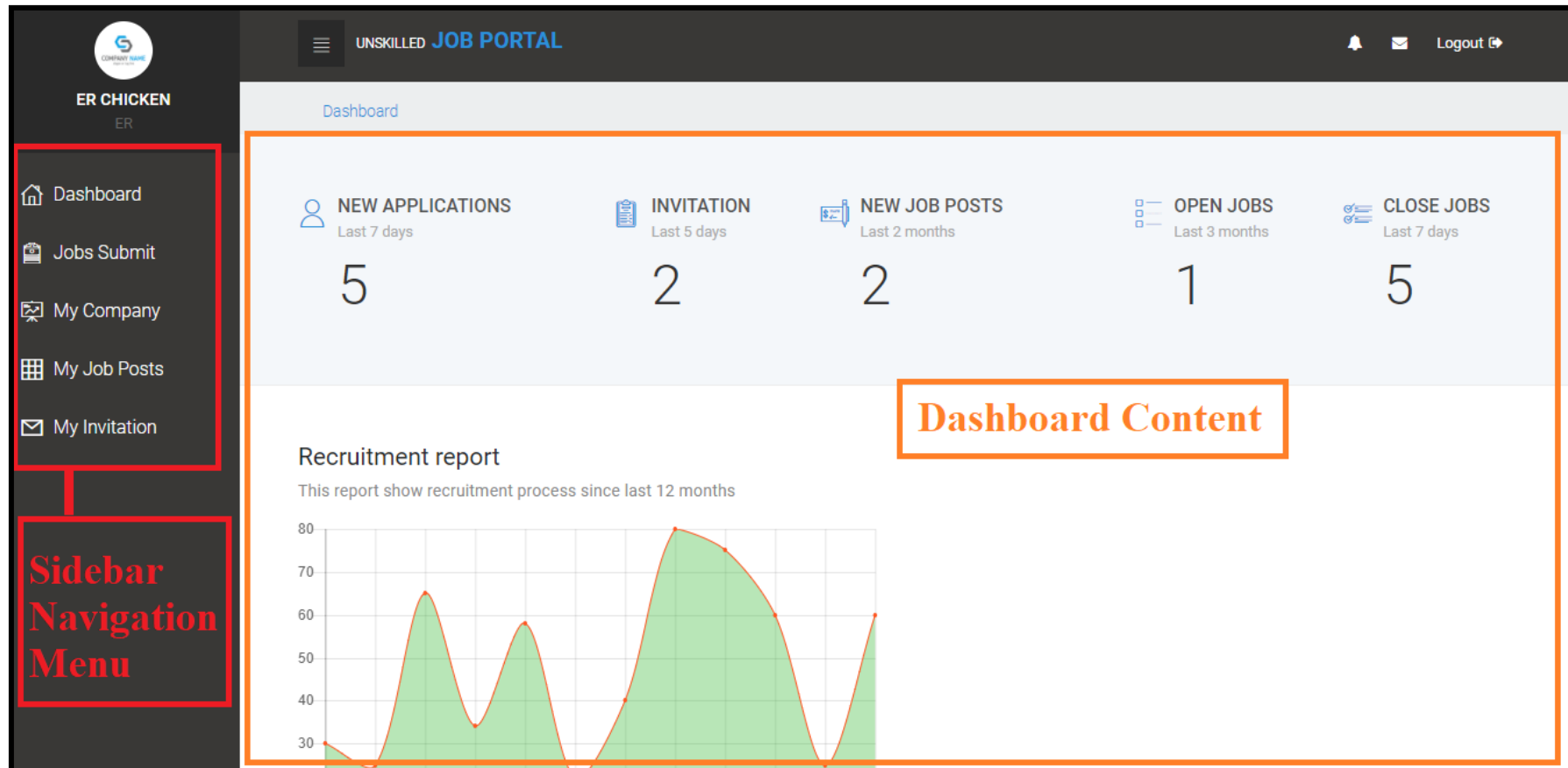


Figure 5.11: Employer's dashboard page.

Figure 5.12 and 5.13 show the employer's job submit page one and two respectively. These two pages have the same left sidebar navigation menu buttons as on employer's dashboard page in Figure 5.11. The main difference of employer's job submit page is that there is job submission form one and two. In job submission form one, employers need to enter their details of job offers, such as job titles, salary, job descriptions, and choose the selection criteria for the job positions before entering job submission form two. In job submission two, employers need to assign the importance of weight for each selection criterion which is chosen from job submission form one by using linguistic terms.

Figure 5.14 shows the employer's my company page. This page has the same left sidebar navigation menu buttons like employer's dashboard page in Figure 5.11. The main difference of this page is that there is companies' details update form. In companies' details update form, employers are allowed to update their companies' details such as company names, email addresses, passwords and company's description.


ER CHICKEN
ER

Dashboard

Jobs Submit

My Company

My Job Posts

My Invitation

Sidebar
Navigation
Menu

Job Submission Form

Job Submission Form One

Job Title

Offer Salary (day)

RM

.00

Job Description

Selection Criteria

☐Independent

☐Diligent

☐Responsible

☐Honest

☐Punctuality

☐Efficient

☐Cooperative

☐Confidence

☐Procedural

☐Intuitive

☐Flexibility

☐Easy Going

☐Experience

☐Energetic

☐Curiosity

☐Approachable

☐Patient

☐Friendly

☐Cheerful

☒Cost

*You can choose multiple criteria

Next

Unskilled Job Portals © 2017

Powered & Design by Unskilled Job Portals

Figure 5.12: Employer's job submit page one.



ER CHICKEN
ER

- Dashboard
- Jobs Submit
- My Company
- My Job Posts
- My Invitation

Sidebar Navigation Menu

Dashboard / Jobs Submit

Job Submission Form Two

Job Submission Form

Linguistic Value	Very Poor	Poor	Medium Poor	Fair	Medium Good	Good	Very Good
Value	1	2	3	4	5	6	7

1) Procedural

1 ★ ★ ★ ★ ★ ★ ★ 7

2) Patient

1 ★ ★ ★ ★ ★ ★ ★ 7

3) Flexibility

1 ★ ★ ★ ★ ★ ★ ★ 7

4) Cost

1 ★ ★ ★ ★ ★ ★ ★ 7

Save

Go Back

Assign Importance of Fuzzy Weight for each criterion by using fuzzy linguistic terms

Unskilled Job Portals © 2017

Powered & Design by Unskilled Job Portals

Figure 5.13: Employer's job submit page two.

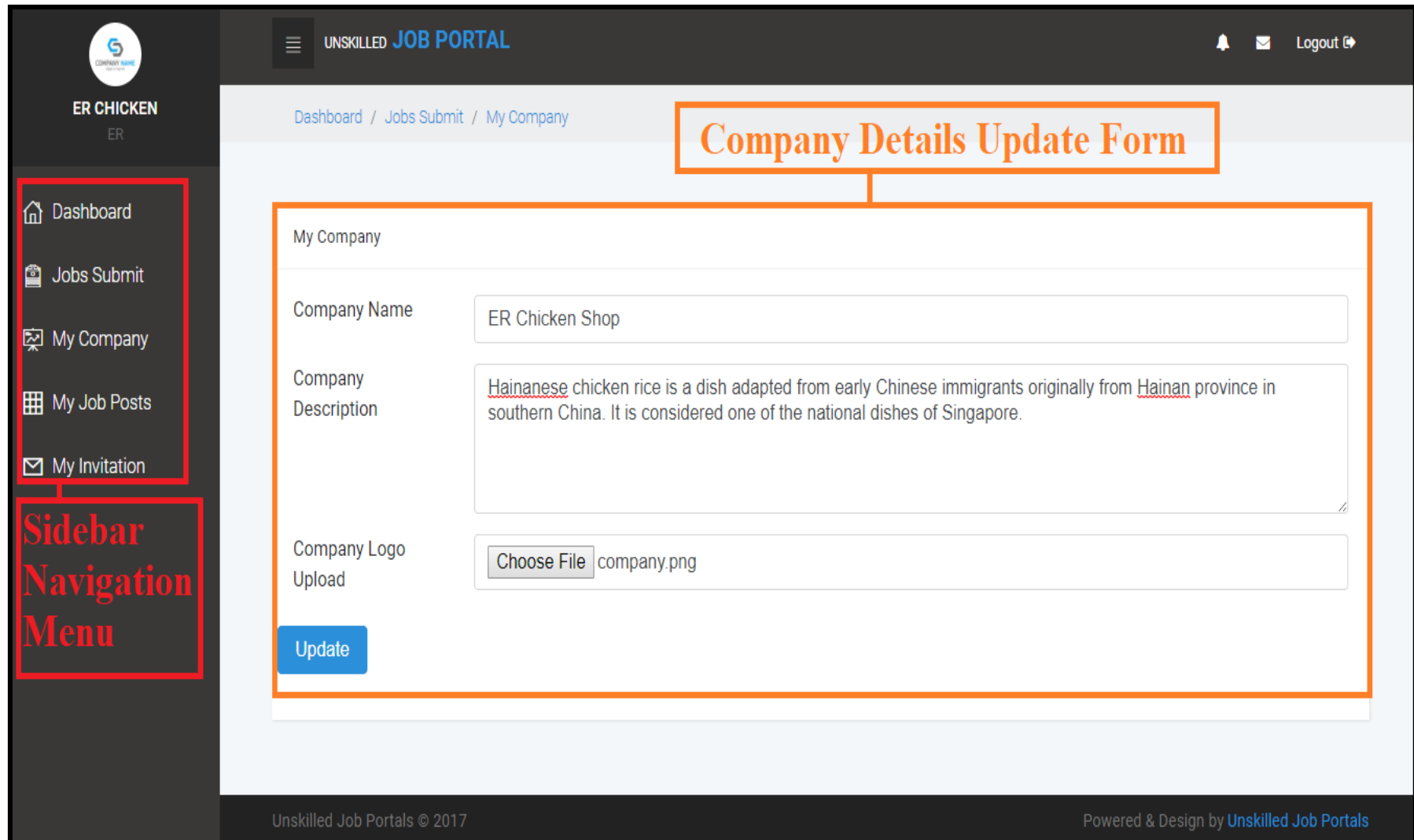


Figure 5.14: Employer's my company page.

Figure 5.15 shows the employer's my job posts page one. This page has the same left sidebar navigation menu buttons like employer's dashboard page in Figure 5.11. The main difference of this page is there is a list of job offers from employers themselves. In the list of job offers, employers are allowed to check the jobs' details such as job titles, salaries and job's descriptions. Additionally, employers can find the recommended candidates by using the blue action button which is get best candidate button before employer's my job posts page two pops out.

Figure 5.16 shows the employer's my job posts page two. This page has the same left sidebar navigation menu buttons like employer's dashboard page in Figure 5.11. After employers use the get best candidate action button, the results of recommended candidates are displayed below the list of job offers. From the results of recommended candidates, it displays some information about the job offers, such as job titles, salaries, descriptions and selection criteria for the job positions.

Figure 5.17 shows the employer's my job posts page three. This page has the same left sidebar navigation menu buttons like employer's dashboard page in Figure 5.11. There is a top three recommended candidates section below the results of recommended candidates in Figure 5.16. From the top three recommended candidates section, it allows employers to check the rating scores of the candidates before hiring the candidates by using the hire action button.



ER CHICKEN
ER

Dashboard

Jobs Submit

My Company

My Job Posts

My Invitation

UNSKILLED JOB PORTAL

Dashboard / Jobs Submit / My Company / My Job Posts

Lists of Job Posts

My Job Lists

#	Job Title	Salary	Description	Action
1	Promoter	RM 90	Sampling	Get Best Candidate
2	Waiter	RM 900	Serve Customer	Get Best Candidate
3	Cleaner	RM 650	Clean house weekly	Get Best Candidate
4	Cleaner	RM 90	Clean my house weekly	Get Best Candidate
5	Food Deliver	RM 80	Deliver food to certain area. We will provide transportation (motorcycle).	Get Best Candidate

Unskilled Job Portals © 2017

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Figure 5.15: Employer's my job posts page one.



ER CHICKEN
ER

- Dashboard
- Jobs Submit
- My Company
- My Job Posts
- My Invitation

Sidebar Navigation Menu

5

Food Deliver

RM 80

Deliver food to certain area. We will provide transportation (motorcycle).

Get Best Candidate

Job Title: Promoter

Unskilled

Available

Job Salary Offer (Day): RM 90.00

Sampling

Results of Best Candidate- Details of Jobs

Selection Criteria

independent	VL
• honest	VL
confidence	VL
procedural	VL
approachable	VL
cost	VL

Figure 5.16: Employer's my job posts page two.

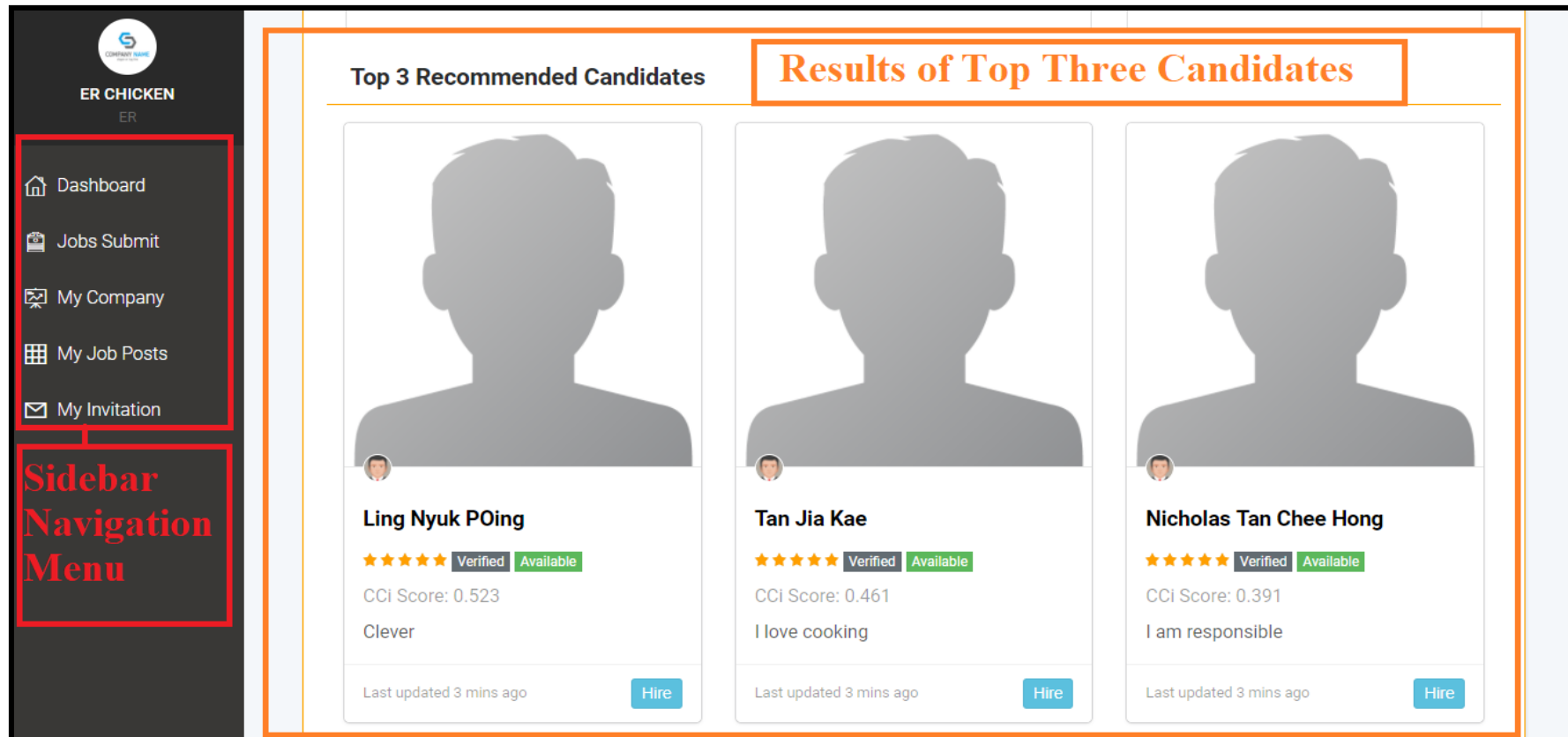


Figure 5.17: Employer's my job posts page three.



ER CHICKEN
ER

Dashboard

Jobs Submit

My Company

My Job Posts

My Invitation

Sidebar
Navigation
Menu

UNSKILLED JOB PORTAL

Logout

Dashboard / Jobs Submit / My Invitation

Lists of Invitation for Job Posts

My Invitation

No	Full Name	Job Title	Invitation Date	Status	Action
1	Tan Jia Kae	Cleaner	7 July 2017	Rejected	X
2	Ling Nyuk POing	Cleaner	7 July 2017	Success	X

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Figure 5.18: Employer's my invitation page.

Figure 5.18 shows the employer's my invitation page. This page has the same left sidebar navigation menu buttons as the employer's dashboard page in Figure 5.11. In this page, there is a list of job candidate invitation in the middle of the page. This list of job candidate invitation shows all the invited candidates for particular job offers. Employers can check the invitation status for each candidate.

5.2 Conclusion

This proposed system consists of two types of users, first type of users is job seekers who are looking for jobs, and the second type of users is employers who are offering the job, and they are looking for the job seeker. Job seekers are allowed to register, login and apply a suitable job which are fit into their preference, whereas employers allowed to register, login, submit job offers, and hire relevant job seekers who are best fit with the job requirements. This proposed system implemented F-TOPSIS algorithm as the filtering technique to recommend the best candidate for job recruiter whereas suggest the most suitable job for the job hunter. Besides, the selection criteria is chosen based on Kansei Engineering Model from big five personality traits. Moreover, the graphic user interface is designed based on the Shneiderman's Eight Golden Rules.

CHAPTER 6

CONCLUSIONS AND FUTURE WORKS

6.0 Introduction

This chapter highlights the contributions of this study, summarizes the main finding of this study, and the conclusion.

6.1 Contributions

The contributions of this study are:

- i. To propose the use of Kansei engineering approach to identify criteria that are the most relevant for the selections of unskilled workers in different job sectors.
- ii. To employ a fuzzy criteria framework that uses the job criteria identified for job candidate rankings.
- iii. To develop a web-based system implementing the proposed fuzzy multi-criteria ranking of job candidates.
- iv. To propose an alternative AI technique that implementing the proposed fuzzy multi-criteria filtering technique which can be used in recruitment of Human Resource Information System (HRIS).

6.2 Summary on Findings

The findings of this study are summarised:

- i. E-recruitments benefit both human resource recruiters and job seekers because of its cost, effectiveness, time-savings characteristics and accessibility

- ii. Traditional online recruiting portals normally apply only simple Boolean operations to compare the requirements from both employers and job candidates.
- iii. Boolean search is insufficient in recommending the best and qualified candidate in recruitment processes because Boolean search will return all the candidates who have exactly same results from the keywords from recruiters, and it has difficulties in presenting the ratings of each candidate.
- iv. Defined criteria for recruitments of unskilled workers based on the personality traits with the Kansei Engineering (KE), and applied the F-TOPSIS algorithm to calculate the better closeness coefficient to recommend the best candidate to be recruited the unskilled workers without any resume or cover letter.
- v. Most unskilled employers are willing to accept unskilled workers who do not have “experience” but he or she must be a “responsible” worker.
- vi. Applying F-TOPSIS algorithm to calculate the better closeness coefficient is suitable to recommend the best candidate for recruitments of unskilled workers.

6.3 Conclusion

E-recruitment systems have become the main recruitment channels in most of the organizations nowadays. It does not only become a new trend in recruitment techniques but also a popular choice for HRM practitioners. Choosing and tracking the candidates normally depend on different kinds of criteria, for instance, necessary skills, commitment to work, willingness for working duties, several of personality traits and etc. Therefore, MCDM method becomes the superior scheme to hire the most advisable and adequate employee for a company. Meanwhile, integrating fuzzy set theory with MCDM enables the recruitment system to deal with the uncertainty and the ambiguity (Varmazyar & Nouri, 2014). Thus

FMCDM is able to make the recruitment system receive the configuration of multi criteria selection problem of employers and employees.

In between HRM and the employees of a company, recruitment is always the main phase in the long-term assurance (Florea, 2014). This is because it is the procedure of trying to discover and embolden potential job seekers to apply for an employment from the company. Employing a suitable applicant for a job offer is hypothetical to achieve high in a company. It is always the main concern for a company (Sarda et al., 2014). It is principled to be employed within the company. The quality of the employment is the consequence of suitability between the applicants and the demands for the company. The key decision for the quality for the e-recruitment is based on candidate filtering and candidate ranking process (Florea, 2014). Candidate ranking is the method to calculate and allocate scores to applicants (Faliagka et al., 2012). However, traditional online recruiting portals normally apply only simple Boolean operations to compare the requirements from both employers and job candidates, and this simplistic method returns many false hits.

Apart from that, the unemployment rate among people in Malaysia is an authentic issue. The national unemployment rate is at 3.5 percent, and the total unemployment rates for unskilled workers shoots up to 10.7 percent in 2009 (Hanapi & Nordin, 2014). This directly implies that the unskilled workers meet problem on getting the jobs. Additionally, researchers discovered a gap in the market for unskilled worker hunting. There are many unskilled workers hard to get an unskilled job. Generally, there are a lot of unskilled workers have to go door-to-door to be hired for unskilled job because there are not much unskilled job listings

provided by the existing job portals. This shows that how serious the ignorance of unskilled jobs in our society. Therefore, this research is to solve this issue.

Being brought about in the chapter one, the main objective of this study was achieved. This is because the primary objective for this research is developing a fuzzy system for online recruitment selection of unskilled workers. The FMCDM that the researcher applied is F-TOPSIS algorithm to recommend and rank the best candidate through multiple selection criteria. On the other hand, another two specific objectives were also achieved. One of the specific objectives was to identify the prominent personality traits that are preferred by employers in different unskilled job categories in Malaysia. KE methodology is applied to determine the most preferred personality traits for different unskilled job sectors. Six unskilled job sectors are covered in this research, which are construction, hotel, manufacturing, restaurant, sales and marketing, and service sectors. Another specific objective is to develop a framework for the recruitment selection by using personality traits and fuzzy system. An e-recruitment system is developed for recruitments of unskilled workers, and the selection criteria are based on personality traits. Graphic user interface for this framework is illustrated in chapter five.

Furthermore, there are two research questions were made explicit in chapter one. The first research question was “Is FMCDM where selection criteria are defined from KE suitable to filter and match the unskilled candidates in recruitment system without any resume, certificate and cover letter submission?”. Developing a fuzzy system for online recruitment selections of unskilled workers was used to address this research question. A case study is

presented in this dissertation in which a private sales and marketing unskilled company- Company A is considered as the case company.

Five human resource experts (human resource manager or recruiter who has at least three years' working experience in human resource area) from Company A. Evaluation takes place by using hamming distance method algorithm and ranking from experts (DM groups) to compare the result from F-TOPSIS. Cohen's Kappa coefficient is calculated in order to get the inter-rater reliability among both evaluation methods with F-TOPSIS. Based on the evaluation result, F-TOPSIS is a suitable proposed solution for recommending and ranking of unskilled job seekers because the inter-rater reliability between F-TOPSIS and hamming distance method, and the inter-rater reliability between F-TOPSIS and experts (DM group) are satisfying. Hence, FMCDM where selection criteria are defined from KE is suitable to filter and match the unskilled candidates in the recruitment system without any resume, certificate and cover letter submission.

The second research question was "What are the prominent personality traits that are preferred by employer and recruiters in different kinds of unskilled sectors in Malaysia?". In order to get the most prominent KW that are preferred by employers and recruiters in different kinds of unskilled sectors in Malaysia, KE methodology was implemented. The ratings of twenty KWs for different unskilled industries were illustrated in chapter four. From the result of ratings of twenty KWs for different unskilled industries, it shows that the "cost" is the most prominent KW for construction, "responsible" and "friendly" are the most prominent KWs for hotel, "responsible" is the most prominent KW for manufacturing,

“cooperative” is the most prominent KW for restaurant, “independent” is the most prominent KW for sales and marketing, and “responsible” is the most prominent KW for service sector.

Other than that, the main struggling and challenging part in this research is on the selecting the FMCDM approach. This is because the correct and suitable FMCDM algorithm played the most important role in recommending and ranking of unskilled job candidates in the proposed system. In order to decide the suitable FMCDM approach, the literature related to FMCDM approaches was explored in chapter two. Additionally, comparison among the FMCDM approaches were also discussed in chapter two so as to choose the relevant and adequate FMCDM in order to recommend and rank the unskilled workers.

In conclusion, the proposed system applied F-TOPSIS as the fuzzy system to do the unskilled job candidate filtering, recommending and ranking. A web platform with fuzzy system was developed by the researcher using web programming language such as PHP, JAVASCRIPT and MySQL with the help of journals, books, articles and the supervisor.

6.4 Future Works

This proposed system can do the unskilled job candidate filtering, and recommend the best candidates to employers based on different selection criteria. However, there are some improvements could be considered in the future. Firstly, the selection criteria that were defined by KE only cover the personality traits. Therefore, the selection criteria may include other aspects that can be used to judge and evaluate the unskilled workers. Secondly, this research only covers the big common and popular unskilled job sectors in Malaysia, they are construction, hotel, manufacturing, restaurant, sales and marketing, and service sectors.

Therefore, it should be covered as much the unskilled job sectors in Malaysia by discovering private and hidden unskilled job categories in Malaysia.

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APPENDICES

Appendix A – Existing Job Portal in Southeast Asia

No	Job Portal Name	Job Portal URL
1	JobStreet	https://www.jobstreet.com.my/
2	Springasia	https://www.springasia.com/
3	Naukri	https://www.naukri.com/
4	JobMalaysia	http://www.jobsmalaysia.gov.my/
5	Looking4Job	http://looking4job.net/
6	BestJob Malaysia	https://www.bestjobs.com.my/
7	Jobcental	http://jobscentral.com.sg/
8	Monster	https://www.monster.com/
9	KareerKo	http://www.kareerko.com/
10	Jenjobs	https://www.jenjobs.com/
11	indeed	https://www.indeed.com/
12	Maukerja	https://www.maukerja.my/
13	Recruit.net	http://malaysia.recruit.net/
14	mystarjob	http://mystarjob.com/
15	CareerJet	https://www.careerjet.com/
16	SPA	http://www.spa.gov.my/
17	bdJobs	http://www.bdjobs.com/
18	GlassDoor	https://www.glassdoor.com/
19	Malaysia Job	https://malaysia.craigslist.org/
20	Jobcity	https://www.jobcity.my/
21	Charkri	http://www.chakri.com/
22	Jobhouse	https://jobhouse.com.gh/
23	Kerjaya org	https://kerjaya.org/
24	Startup Job	http://my.startupjobs.asia/my/
25	Daijob	https://www.daijob.com/en/
26	Jobspot	http://jobspot.lk/
27	ZipRecruiter	https://www.ziprecruiter.com/
28	JobsDB	https://sg.jobsdb.com/sg
29	GigaJob	https://www.gigajob.com/

Appendix B – Contingency table for proposed solution and hamming distance

Hamming Distance	F-TOPSIS																				Total
	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20	
A1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
A2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A4	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
A5	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
A6	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
A7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A9	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1

A10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A11	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
A12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1
A16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1
A18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1
A19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
A20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Total	1	0	0	1	1	0	1	0	1	0	1	0	0	0	1	0	1	1	1	0	10

Appendix C – Contingency table for proposed solution and decision making group (experts)

Experts	F-TOPSIS																				Total
	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20	
A1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
A3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A5	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
A6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A7	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
A8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A9	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1

A10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A11	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
A12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A14	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
A15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1
A16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
A17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1
A18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1
A19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Total	1	0	0	1	1	0	1	0	1	0	1	0	0	0	1	0	1	1	1	0	10

Appendix D – List of publication

1. Tan, J. K., Lee, N. K., Bong, C. H., & Ahmad Sofian, S. Identification of Personality Traits for Recruitment of Unskilled Occupations using Kansei Engineering Method. *Journal of Telecommunication, Electronic & Computer Engineering (JTEC)* (Accepted).